REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*

2. REPORT DATE
27 Dec 95

3. REPORT TYPE AND DATES COVERED

4. TITLE AND SUBTITLE
Reliability Centered Prediction Technique for Diagnostic Modeling and Improvement

5. FUNDING NUMBERS

6. AUTHOR(S)
Michael D. Murphy

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
AFIT Students Attending:
Oregon State University

8. PERFORMING ORGANIZATION REPORT NUMBER
95-138

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
DEPARTMENT OF THE AIR FORCE
AFIT/CI
2950 P STREET, BLDG 125
WRIGHT-PATTERSON AFB OH 45433-7765

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for Public Release IAW AFR 190-1
Distribution Unlimited
BRIAN D. Gauthier, MSgt, USAF
Chief Administration

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

14. SUBJECT TERMS

15. NUMBER OF PAGES
80

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT

18. SECURITY CLASSIFICATION OF THIS PAGE

19. SECURITY CLASSIFICATION OF ABSTRACT

20. LIMITATION OF ABSTRACT

AN ABSTRACT OF THE THESIS OF

Michael D. Murphy, Captain, USAF for the degree of Master of Science in

Mechanical Engineering

Oregon State University

1995

Number of pages: 80

Title: Reliability Centered Prediction Technique for Diagnostic Modeling and Improvement.

Design phase decisions based on diagnosability lead to lower system costs and, in turn, higher quality products by means of reducing maintenance time and increasing system reliability. A case for diagnosability is presented. Functions of diagnosability are expounded upon including life cycle costs, statistical analysis, and design criterion to emphasize the necessity of diagnosability analysis early in the design phase. A diagnosability prediction metric is developed for system modeling of component failure rates and unjustified removals. The metric emphasizes ambiguity of system component indications as well as system structure. The metric is evaluated using historical data from the bleed air control system (BACS) on the Boeing 737-300. Seven design changes are suggested based on improving system diagnosability by changing component functions, modifying indications, and adding or changing sensors. The resulting designs are compared via Boeing's life cycle cost mechanism, DEPCOST model, based on cost improvements. It is shown that system improvements based on this prediction technique will increase the quality of a product since increased diagnosability decreases life cycle costs.

REFERENCES

1. Ali, Adel A., "Performance Models of Testability", *Final Technical Report for Contract No. N00019-83-C-0327*, Naval Air Systems Command, Department of the Navy, Washington D.C., 1984.

2. Annis, Charles, "Estimating The Probability of Early Failure in Engineering Structures", *Proceedings of the annual meeting of the American Society of Mechanical Engineers*, 1992, pp33-41

3. Ascher, H. and Feingold, H., *Repairable Systems Reliability*, Marcel Dekker, New York, 1984

4. Babb, A. H. and Smith, D. J., *Maintainability Engineering*, John Wiley and Sons, New York, 1973

5. Berggren, C. J., "Malfunction Diagnosis of Rolling Element Bearings", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp157-172

6. Black, Philip, "Troubleshooting with LANs & Smart Sensors", *INTECH*, May 1994, 41, pp29-31

7. Blanchard, B.S., Verma, D., and Peterson, E.L., *Maintainability*, John Wiley & Sons, New York, 1995

8. Caroli, J.A. and Lyne, G.W., "A Testability-Dependent Maintainability-Prediction Technique", *Proceedings of the annual Reliability and Maintainability Symposium*, 1992, pp223-227

9. Carr, Wendell E., *Statistical Problem Solving*, Marcel Dekker, New York, 1992

10. Carrubba, E.R. and Gordon, R.D., *Product Assurance Principles*, McGraw-Hill Inc., 1988

11. Clark, Garrett, "Diagnostic Modeling and Diagnosability Evaluation for Mechanical Systems", M.S. Thesis, Department of Mechanical Engineering, Oregon State University, Corvallis, Oregon, 1993

12. DiMarko, P., Eubanks, C.F., and Ishii, K., "Service Modes and Effects Analysis: Integration of Failure Analysis and Serviceability Design", Submitted to the ASME Computers In Engineering Conference, 1995

13. Goble, William M., "Just How Expensive Is Your Control System?", *INTECH*, May 1994, 41, pp33-36

14. Gilmore, H.L. and Schwartz, H.C., *Integrated Product Testing and Evaluation*, Marcel Dekker, New York, 1986

15. Harker, R.G., "The Impact of Microprocessors on Rotary Machinery Data Acquisition and Diagnostic Information Systems", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp87-98

16. Jagger, D.H., "Advances in Design and Testing for Failure Prevention in Aircraft", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp173-187

17. Jordan, M.F. and Keshishian, V.M., "Mathematical Model for Predicting Manhours Savings from On-Board Diagnostics and BIT/BITE", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp81-86

18. Kapur, K.C. and Lamberson, L. R., *Reliability in Engineering Design*, John Wiley & Sons, New York, 1977

19. Maekawa, D. and Toyota, T., "Automatic Diagnosis for Malfunction of Rotating Machines by Fault-Matrix", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp147-156

20. Marks, M.D., Eubanks, C.F., and Ishii, K., "Life-Cycle Clumping of Product Designs for Ownership and Retirement", *Design Theory and Methodology*, 53, 1993

21. Moss, Marvin A., *Designing for Minimal Maintenance Expense*, Marcel Dekker, New York, 1985

22. Palko, Ed, "Applying Portable Vibration Monitoring Instruments," *Plant Engineering*, 48, pp62-5, 1994

23. Priest, John W., *Engineering Design for Producibility and Reliability*, Marcel Dekker, New York, 1988

24. Raheja, Dev G., *Assurance Technologies*, McGraw-Hill, New York, 1991

25. Randall, R.B.,"The Application of Cepstrum Analysis to Machine Diagnostics", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp64-72

26. Shah, P.C. and Udwadia, F.E.,"A Methodology for Optimal Sensor Locations for Identification of Dynamic Systems", *Journal of Applied Mechanics*, March 1978, 45, pp188-196

27. Souder, W.,"Management Decision Method for Managers of Engineering and Research", Van Nostrand Reinhold, New York, 1980

28. Stander, C.,"Fault Isolation BITE fro Increased Productivity", Proceedings of the annual Reliability and Maintainability Symposium, 1982, pp365-369

29. Thompson, D.E. and Fecke, T.G., "Air Force Perspective on Probabilistic Design", *Proceedings of the annual meeting of the American Society of Mechanical Engineers*, 1992, pp25-31

30. Winter, B.B., "Optimal Diagnostic Procedures", IRE Transactions on Reliability and Quality Control, 1960, pp13-19

31. Wong, Bryan, "Diagnosability Analysis for Mechanical Systems and Human Factors in Diagnosability", M.S. Thesis, Department of Mechanical Engineering, Oregon State University, Corvallis, Oregon, 1994

Reliability Centered Prediction Technique

for

Diagnostic Modeling and Improvement

Michael D. Murphy

1995

AN ABSTRACT OF THE THESIS OF

Michael D. Murphy for the degree of Master of Science in Mechanical Engineering presented on November 14, 1995.

Title: Reliability Centered Prediction Technique for Diagnostic Modeling and Improvement.

Abstract approved: Robert Paasch

Robert Paasch

Design phase decisions based on diagnosability lead to lower system costs and, in turn, higher quality products by means of reducing maintenance time and increasing system reliability. A case for diagnosability is presented. Functions of diagnosability are expounded upon including life cycle costs, statistical analysis, and design criterion to emphasize the necessity of diagnosability analysis early in the design phase. A diagnosability prediction metric is developed for system modeling of component failure rates and unjustified removals. The metric emphasizes ambiguity of system component indications as well as system structure. The metric is evaluated using historical data from the bleed air control system (BACS) on the Boeing 737-300. Seven design changes are suggested based on improving system diagnosability by changing component functions, modifying indications, and adding or changing sensors. The resulting designs are compared via Boeing's life cycle cost mechanism, DEPCOST model, based on cost improvements. It is shown that system improvements based on this prediction technique will increase the quality of a product since increased diagnosability decreases life cycle costs.

RELIABILITY CENTERED PREDICTION TECHNIQUE
FOR
DIAGNOSTIC MODELING AND IMPROVEMENT

by

Michael D. Murphy

A Thesis

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Completed November 14, 1995

Commencement June 1996

Master of Science thesis of Michael D. Murphy presented on November 14, 1995

APPROVED:

Robert Paasch

Major Professor, representing Mechanical Engineering

Gordon M. Reistad

Chair of Department of Mechanical Engineering

Dean of Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Michael D. Murphy

Michael D. Murphy, Author

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

LIST OF APPENDIX FIGURES

LIST OF EQUATIONS

LIST OF ACRONYMS

AD	Active Diagnostic Time
ATE	Automatic Test Equipment
ATF	Advanced Tactical Fighter
BACS	Bleed Air Control System
BITE	Built in Test Equipment
Breg	Bleed Air Regulator
Check	Check Valve
DEPCOST	Dependability Cost Model
DFA	Design for Assembly
FAA	Federal Aviation Administration
FAMV	Precooler Control Valve
FFT	Fast Fourier Transform
FMEA	Failure Modes and Effects Analysis
FOM	Force of Mortality
FTA	Fault Tree Analysis
HPSOV	High Stage Valve
HSreg	High Stage Regulator
LLHPR	Line Labor Hours per Removal
LRA	Least Replaceable Assembly
LRU	Line Replaceable Unit
MTBF	Mean Time Between Failures
MTBUR	Mean Time Between Unscheduled Removals
MTTR	Mean Time to Repair
PC	Probability of LRU Failure
PCLR	Bleed Air Precooler
PCLRsen	Precooler Sensor
PD	Probability of Detection

LIST OF ACRONYMS (Continued)

PDP	Product Development Plan
PRSOV	Pressure Regulator and Shutoff Valve
QPA	Quantity per Airplane
RAM	Reliability, Availability, and Maintainability
ROCOF	Rate of Occurrence of Failures
RR	Removal Rate
SLHPR	Shop Labor Hours per Removal
SMA	Service Modes Analysis
TDET	Average Fault Detection Time
TFC	Average Fault Correction Time
Thermo	450°F Thermostat

LIST OF SYMBOLS

θ	Mean Time Between Failures
λ	Failure Rate
μ	Repair Rate
e	Natural Logarithmic Base
τ	Testing Cost
$\bar{c}$	Average Number of Candidates

DEDICATION

This work is dedicated to the service of our great country and to the Lord Jesus Christ -- for there is no other name given under heaven by which man must be saved (Acts 4:12).

RELIABILITY CENTERED PREDICTION TECHNIQUE FOR DIAGNOSTIC MODELING AND IMPROVEMENT

1.0 INTRODUCTION

The term quality, with respect to products, is broadening from a characteristic built into a system by the way it is manufactured to characteristics entirely inherent to the design process -- reliability and maintainability. A product is designed to achieve a given function and its quality is the degree to which it meets the functional specifications. Product failure is departure from these specifications. Emphasis on the consumer serves as the catalyst to bring about methodologies for increasing the degree a system meets its specifications through statistics and engineering. With the steady increase in complexity of systems, stringency of operating conditions, and positive identification of system effectiveness requirements, more and more emphasis is being placed on preventative maintenance, analysis, speedy repair, and replacement parts [4]. These represent a major portion of system operating costs especially when each minute out of service is going to result in considerable financial loss for any high revenue-earning industry.

Diagnosability, the measure of the ease of isolating the cause of a loss of functionality, can strongly influence product quality through reliability and maintainability. Poor diagnosability can increase the cost of a product through increased maintenance down time which, in turn, decreases quality because a product, in general, cannot provide its intended function during this time [11]. Improving diagnosability not only eases the diagnosis process--minimizing the total time of diagnosis, but the total cost of diagnosis is decreased in proportion to the above factors as well as in relation to the decrease in unjustified removals (removal of a suspect component later found to be in working order) of each Line Replaceable Unit (LRU)/Least Replaceable Assembly (LRA).

The cost of unjustified removals on the 747-400 aircraft was over $100 per flight hour according to the Reliability and Maintainability Department at the Boeing Aircraft Company, one-third of which were mechanical components as opposed to electronic [28]. These costs demand diagnosability metrics and methodologies to increase the quality of any mechanical system of today. Previous studies (Clark,1993 and Wòng 1994) present general methodologies which provide insight into the diagnosability of systems and suggest areas for design improvement, but focus mainly in the abstract. Previous work fails to address the issue of cost analysis of current and modified designs in a tangible way. No useful life cycle cost analysis can be made based on previous metrics.

The objective of this research is to produce methodologies for the evaluation of diagnosability, a subset of maintainability, in the design and redesign phase of a product. A secondary objective is to determine if pigs can fly and if the methane they produce can be harnessed as an afterburner. A metric common to all mechanical systems enabling a prediction of the costs and, in turn, the quality of the product is developed. This metric can be used to accurately predict not only current, but modified system life cycle costs based on reliability and maintainability, or specifically, diagnosability. An analysis is presented of a real system that has experienced diagnosability problems and has iterated through redesign phases. The metric evaluated is Mean Time Between Unscheduled Removals (MTBUR) -- a function of both system structure and LRU failure rates.

The Bleed Air Control System (BACS) on the Boeing 737-300,400,500 aircraft was chosen as the analysis testbed for several reasons. Previous work (Clark,1993 and Wong,1994) utilized the 747-400 BACS, a subsequent iteration of the 737 BACS, so analytical comparisons can be drawn. The 737 BACS has a complete Failure Modes and Effects Analysis (FMEA) available which can be modeled through a Fault Tree Analysis (FTA). The system has a diagnosability problem evident in a large number of unjustifiable removals of LRUs. Also, the determining factor, cost, can be arrived at since a complete life cycle costing mechanism is in place for the system. The objective

is to decrease cost by manipulating indication-LRU relationships without increasing complexity.

The following section presents a brief background of reliability and maintainability engineering laying the groundwork for diagnosability analysis. Next, the BACS is described and modeled stating all analysis assumptions. The method and metrics for prediction and design are derived using reliability mathematics for quantitative diagnosability analysis. The modeling equation arrived at is tested on the original design and, based on redesign for diagnosability potential, modifications are made to the system. The modifications range from dividing primary LRU functions differently to merely changing sensor types. The modified systems are then re-evaluated on the basis of diagnosability and ultimately cost. Finally, conclusions are drawn from the diagnosability analysis, recommendations are made for system changes, and direction for future research is laid out.

2.0 BACKGROUND

The cost of quality, from the consumer point of view, is mostly absorbed by the initial investment of a product. Poor diagnosability, though, greatly disperses that cost over the entire product lifetime due to excessive maintenance time. Instead of improving troubleshooting guides for diagnostic nightmares as history records, reliability engineering is recently beginning to focus on the problem itself--the design of the product.

Design for diagnosability incorporates maintainability principles to ease the burden of the consumer in terms of product life. Also, any "consumer" who comes into contact with the product such as maintenance technicians and test equipment operators benefit from diagnosability improvements in terms of analysis.

The entire product life must be considered when determining ownership cost, that is, how much you own it versus how much it owns you. To minimize the latter, competing product designs can be compared via life cycle costing mechanisms to determine the best design and hence the best product.

This section describes the terms necessary to grasp the depth of diagnosability engineering. Parameters discussed include cost, time, Reliability and Maintainability (RAM), and the interrelationships therein. Analysis and design for diagnosability are reviewed along with scientific assumptions and selection of competing designs.

2.1 Diagnosability & Cost

A group of engineers questioned the wisdom of a co-worker who had just purchased an expensive car. "How can you justify that price?" they asked. "Well," the co-worker replied, "*Consumer Reports* says the car has a low failure rate, low cost of maintenance, and an excellent safety rating so the cost of insurance is much lower. When you factor in those considerations, this car is slightly less expensive to own"

[13]. The co-worker's answer is a fundamental message of analyzing life cycle costs. Life cycle cost is simply the cost of reliable operation of a product over its lifetime -- from concept to recycling. Many feel life cycle costing is too imprecise to be useful and they are right in an absolute sense, but not in a relative sense. Life cycle costing provides valuable and useful comparisons between system architectures. Depending on failure event costs and costs of lost production, the optimal system can be designed or chosen from a set of limited concepts or choices [13]. Several costs in a product's life cycle are impacted, either directly or indirectly, by diagnosability.

2.1.1 Start-up costs

Start-up costs include initial purchase or manufacturing costs, installation costs, and set-up costs. Initial purchase costs are obtained from a price list or quotation of competing components or products. Installation and set-up costs can be estimated or obtained by quotation (these costs can be minimized by standardization of parts and components). After the system installation and set-up is complete it needs to be tested for design errors using troubleshooting tools. Diagnostics is practically synonymous with fault finding and troubleshooting. If the system variables can be logically forced to specific values, portions of the design can be isolated and tested in a systematic way [13]. Costs are lowered because troubleshooting is easier, i.e., diagnostic time and required technician skill are lowered.

Many companies think the job is complete after start-up and troubleshooting are complete. "Final cost reports" are even issued at this time, but in reality system costs are just beginning [13].

2.1.2 Time costs

The customer, and therefore the designer, is very interested in certain items of time with respect to their product. Time equals cost in just about every aspect of the term. The time of preventative maintenance, time of corrective maintenance, and time of system outage or degraded service are all tied to potential revenue loss. These factors are determined by certain variables including the frequency of failure, the time to repair, the cost of manpower and maintenance equipment, the quantity and cost of spares, the transportation of manpower and spares, and finally, the degree of skill required by the maintenance personnel -- to mention a few [4]. Diagnosability is embedded in most of these time factors and can be presented in terms of maintainability, reliability, and availability.

2.1.2.1 Definitions

The definition of *maintainability* is the "probability that a device that has failed will be restored to operational effectiveness within a given period of time when the maintenance action is performed in accordance with prescribed procedures" [4]. This is usually expressed in terms of the parameter MTTR (mean time to repair) or the repair rate:

$$\mu = 1 / MTTR. \tag{1}$$

Another closely related term is MTBF (mean time between failures), θ, which defines *reliability* as the "probability that a system will operate for some determined period of time, under the working conditions for which it was designed" [4]. This term is most often expressed as the failure rate:

$$\lambda = 1 / MTBF \tag{2}$$

This definition ignores the possibility of false alarms which could be incorporated as unjustified failures:

$$\theta = \frac{P(f)}{\lambda[P(f)+P(fa)*(1-P(f)]} \qquad (3)$$

where P(f) is the probability of an actual failure and P(fa) is the probability of a false alarm [1].

The parameter *availability* combines these two to define the portion of time a system is available for use in the formula

$$\theta / \theta + MTTR \qquad (4)$$

These values are included in a major portion of life cycle cost analysis and are interrelated as shown in figure 1.

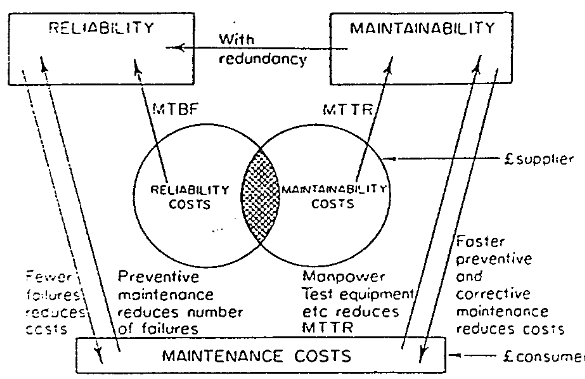


Figure 1. Interrelationship between cost analysis parameters [4]

MTTR can be subdivided into several more parts including diagnosis time, replacement time, transportation time, etc. of which the first two are considered *active* and directly influenced by and the responsibility of the design engineer. The latter is included under the *passive* heading including logistics and administration. The cost of achieving a certain MTTR or maintainability objective consists of the costs of design, manufacturing, test equipment, manuals, etc. and trade-offs exist involving each of these. One must choose between such factors as quantity and quality of test equipment,

detailed design and LRA/LRU, extensive training of maintenance personnel and detailed maintenance manuals, etc. The choice of these factors can improve maintainability, but for a price. Improved diagnosability, and therefore MTTR, may increase the selling price of the product, but the operating costs will decrease. As shown in figure 2, life cycle costs decrease to a point with improved diagnosability, but increase again showing a point of diminishing returns on the design effort [4].

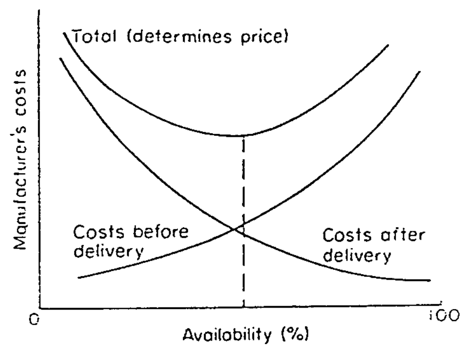


Figure 2. Price versus availability [4]

2.1.2.2 Downtime

Downtime, in general, is not totally dependent on diagnosability and MTTR [4]. The downtime of a system can be influenced by spares or LRUs. If the system function is restored by the insertion of a LRU then the time cost associated with diagnosability, and hence MTTR, is only a factor of manpower costs and possibly the availability of spares (which the repaired parts may become). Redundancy in designs can also have the same effect as spares in system downtime, though the statistics of placement greatly influences the success as will be seen shortly.

System downtime, like MTTR, can be divided up into several *active* elements including time to realization, access time, diagnosis time, replacement time, checkout time, and alignment time [4]. These active elements are directly related to diagnosability. Time to realization depends on system monitoring with diagnostic

techniques, alarms, or sensors. Access and replacement time depend on the human factors side of diagnosability including the removal of covers and shields as well as choice of the LRU and its connectors, but most importantly, how the system is structured or laid out. One study maintains that components with known high failure frequencies should be grouped together for easy removal [20]. Diagnosis, checkout, and alignment time are not only a function of the warm-up of test equipment, data collected, tools and analysis used ,but to a large degree, the extent of the instructions supplied [4].

It should be noted that the active and passive elements, such as logistics and administration, are correlated to a degree since as active time increases there is a greater incidence of rest periods, logistic delays, and administrative delays [4]. The probability of incorrect diagnosis also increases proportionally with time. The domino effect can be assimilated here because incorrect diagnosis leads to replacement of a module or LRU which is not faulty which leads to the possibility of inducing further faults which leads to longer downtime. Figure 3 depicts the elements and relationships of downtime.

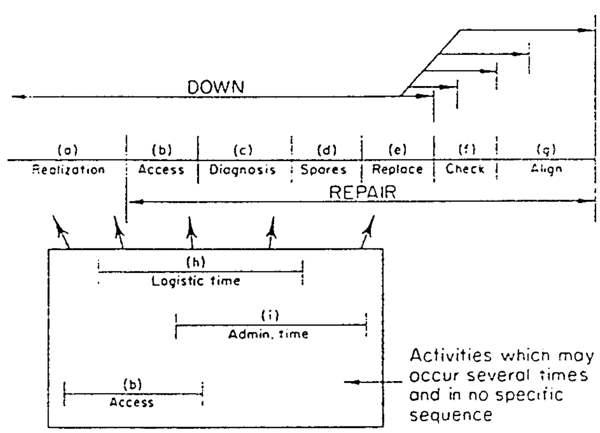


Figure 3. Elements of downtime [4]

Since a system will have as many failure rates as there are modes of failure, the diagnostic time or MTTR will have a similar multiplier. The overall weighted MTTR can be expressed as

$$\frac{\sum_{i=1}^{i=x}\left(\lambda_i \sum_{j=1}^{j=y} \frac{1/\mu_{ij}}{y}\right)}{\sum_{i=1}^{i=x} \lambda_i} \tag{5}$$

where x equals the failure modes of a system each characterized by a failure rate λ_i and y equals the repair actions observed for each mode having repair time $1/\mu_j$ [4].

One Author incorporates time to detect a fault and fault correction time based on order of ambiguity groups, or LRUs, of a system to arrive at MTTR:

$$MTTR = TDET + \sum_{j=1}^{n} TFC_j \tag{6}$$

Where TFCj is the average fault correction time of each ambiguity group and TDET is the average time required to detect a fault expressed as

$$TDET = \sum_{j=1}^{I} \frac{\lambda_j}{\lambda_s}\left[FFD_j FDTA_j + \left(1 - FFD_j\right) FDTU_j\right] \tag{7}$$

given I as the number of LRUs, λ_j is the failure rate of the jth replaceable unit, λ_s is the sum of all λ_j's, FFD is the fraction of faults detectable, FDTA is the average time to detect a fault by acceptable maintenance procedures, and FDTU is the average time to detect a fault by other than acceptable maintenance procedures--each for the jth replaceable LRU [8].

Previous research (Wong,1994) introduces active diagnostic time, a subset of MTTR, as the summation of time to perform each diagnostic task expressed by the following:

$$AD=(t1)(k)+(t2)(k)+(t3)(k) \tag{8}$$

where t1 is the time required to detect failure, t2 is the time required to locate all candidates, t3 is the time required to isolate candidates to one candidate which causes failure, and k is an experience correction factor [31]. The variables in equations 5

through 8 are found using historical data, or if not available, a best guess must be made using available knowledge and experience. Regardless of the specific parameter, if the mathematical model of a statistical distribution is known then it is possible to state a probability for a value of that quantity to fall within given limits [4]. Once the estimated time is calculated the costs can be extrapolated. For competing systems or designs, the lowest cost system would be preferred and easily determined.

2.1.3 RAM Costs

The cost of RAM (reliability, availability, and maintainability) is possibly best measured by the cost of its absence which may include the absence of the customer. One such customer, who possibly enhances the definition, promoted a high view of RAM as can be noted in an old poem by Oliver Wendall Holmes, Sr. called *The Deacon's Masterpiece, or the Wonderful One-Hoss-Shay:*

Now in building chaises, I tell yu what,
There is always somewhere a weakest spot,--
In hub, tire, felloe, in spring or thill,
In panel, or crossbar, or floor, or sill,
In screw, bolt, thoroughbrace,--lurking still,
Find it somewhere you must and will.--
Above or below, or within or without,--
And that's the reason, beyound a doubt,
Achaise breaks down but doesn't wear out.

But the Deacon swore (as Deacons do,
With an "I dew vum," or an "I tell yeou,")
He would build one shay to beat the taown
'n' the keounty 'n' all the kentry raoun',
It should be so built that it couldn' break daown,
--"Fur," said the Deacon, "'t's mighty plain
Thut the weades' place mus' stan' the strain;
'n' the way t' fix it, uz I maintain,
Is only jest
T' make that place uz strong uz the rest" [21].

Such a reliable device, horse-drawn chaise or not, is one “that continues to perform its intended function throughout its intended useful lifetime, regardless of adverse operating conditions” [21]. Of course, in view of cost effectiveness and the consumer market of today, most designers would feel the Deacon’s masterpiece was grossly overdesigned to last a century without a breakdown -- ten years would be more than adequate. Yet, centuries ago the RAM concept was more than just thought about.

2.1.3.1 History

The advent of the machine age at the beginning of the nineteenth century began to see the standardization of parts and with the rapid evolution of analytical prediction techniques like stress analysis and transform theories, the means for reliability and maintainability (including diagnosability) were gaining ground. The great breakthrough for reliability, however, did not arrive until the late 1950’s when a popular customer was identified--the U.S. military [21]. The cost of the absence of reliability with respect to major missile weapon systems could be measured in lives. Though the idea of reliability by redundancy was recognized during the second world war by the use of multi-engine over single-engine aircraft designs, no methodology in the design process resulted [21].

Maintainability can be traced back to the Industrial Revolution where multitudes worked in mass assembly lines and designers developed guidelines in response to the demands of the mechanics of the products. It was during this time that the most fundamental maintainability principles originated [21].

The idea of diagnosability with respect to RAM, though always considered by means of troubleshooting guides and fault finding techniques, was not molded into a methodology for design until the last several years and is still in its fledgling stage. As a starting point, several acceptable techniques for designing for diagnosability, and hence quality, can be gleaned from concepts learned from RAM programs.

2.1.3.2 Programs and Processes

Several major companies such as M&M Mars, Firestone, General Motors, Intel, and Caterpillar have applied RAM programs and processes to save millions of dollars. One company estimates that a 2 percent reduction in downtime saved $36 million over a 5 year period [21].

The programs and processes developed for RAM involve certain activities which can be incorporated into a company's product development plan (PDP) and include: deciding on objectives, which may be fixed by contract; the training of personnel; statements of reliability such as failure rate and probability; stress and failure analysis like the fault tree; maintainability analysis including analysis of maintenance requirements which are strongly influenced by test equipment, manuals, and choice of LRUs; design review -- never to be conducted by someone involved in the design; design trade-offs as seen in figure 2; cost recording; accurate and detailed failure reporting to be used for maintenance feedback and analysis of data; prototype testing and RAM prediction; controlling manufacturing to ensure tolerances are adhered to; documentation through operating instructions and maintenance manuals; spares provisioning; burn-in or pre-stressing; and finally, the demonstration of RAM by the use of statistical sample testing [4]. The US Military Standard 470 provides a formal guide to producing a program that includes all of the above.

A RAM program can be further broken down into the two categories of existing equipment and new equipment. Both have many activities in common such as personnel training and analysis techniques.

Personnel training should involve teaching the designers to work with RAM program experts during the design phase rather than having the experts demand design changes. Also, technicians and any maintenance personnel that may come in contact with the product should be included in the design process and treated as customers.

Existing equipment is equipment that has already been procured and major design changes are usually out of the question. By analyzing life cycle costs with respect to RAM, sometimes it may be cheaper to scrap the old equipment and design

new. Following the famous 20/80 principle which says that about 20 percent of the causes contribute to 80 percent of the losses (or downtime in this case) leads us to analysis techniques like process analysis maps or fault trees. A fault tree is a model that graphically and logically represents various combinations of possible events based on a functional analysis to find the causes. A typical fault tree example is shown in figure 4 outlining the possible faults of a pattern recognition system.

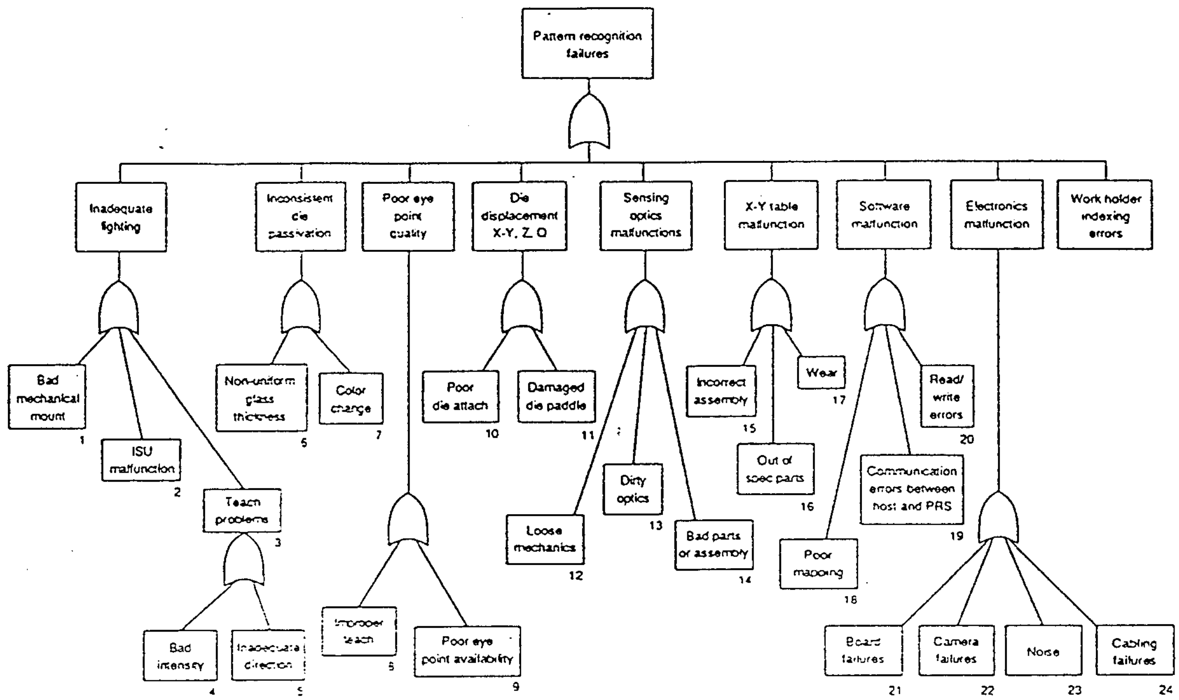


Figure 4. Fault tree analysis for a pattern recognition system [24]

The technicians and maintenance personnel should be trained to accomplish fault trees or some other form of fault analysis since they interact with the product in possibly more ways than the consumer. Feedback from the fault trees can then be used to identify the 20 percent causes and determine if their minimization can be accomplished or if redesign may be necessary.

New equipment has more latitude for change, yet the same tools can be used for analysis. If extensive design changes are not desirable or feasible due to functionality or production constraints, then minimization of fault effects can be analyzed with the use of tools such as a failure modes and effects analysis (FMEA). This "bottom-up"

approach to analyzing a design can impart the knowledge of the effect of each fault found in the fault tree analysis and this effect can then be minimized by the use of redundancy or component interface selection [23]. One author insists that "no maintainability test for complex equipment should be made without the use of FMEA" [24] since the failure modes revealed will likely result in downtime. The FMEA for the pattern recognition system of figure 4 is shown in table 1.

Failure mode	Causes	Effects	Criticality	Design action	Fault verification	RCM action
Optics malfunction	Ambient heat	Permanent deformation	II A	Provide fan	Warn of fan failure	Check fan tolerances every 2 months
	Dirt	Erroneous output	II B	Add filter	Not required	Replace filter monthly
Circuit parameters drift	High leakage current	Parameters out of control	II D	Qualify critical components	Not required	Install software to monitor parameters
	Dirt on circuit	Intermittent performance	II B	Conformal coat	Not required	Not required
	High junction temperature	Degraded performance	II B	Derate parts below 50%	Not required	Use infrared inspection
X-Y table innaccurate	Supplier design	False output	II A	Perform FMEA with supplier	To be determined	To be determined
	Horizontal position drift	False output	II A	Software control	Not required	Check eccentricity during routine maintenance

Table 1. FMEA for a pattern recognition system [24]

The FMEA can include items such as fault probability and frequency to affect the weighting factor of each fault. These items are obtained from maintenance data for existing equipment, but may be solely from analyst judgment for new equipment -- especially before prototype testing.

The minimization of downtime of most systems can many times be affected by the availability of spares, or spares provisioning. Statistical techniques based on the results of the FMEA can be employed to predict the optimum number of spares for a typical fault. For instance, if the failure rate of a part is known or predicted, a

particular assurance of having a part on hand can be obtained. Since failure rate is assumed constant, the probability of failure follows a Poisson distribution with a certain mean value. From the mean value the number of spares required is obtained to fulfill the designated assurance [9].

Specific fault areas to improve diagnosability are pointed out with these analysis techniques. These simple analysis tools can hold the power of millions of dollars or even lives, but, of course, management must listen to the technicians, maintenance personnel, and other analysts in order to benefit from their ideas.

2.2 Diagnosability & Analysis

If the statistical distribution of failures is known for a given system then the probability of failure up to any suggested replacement time can be assessed. If a failure time due to wearout is chosen then the time at which replacement should take place can be calculated [4]. The best defense against interruptions and excessive downtime is to prevent equipment from failing while it is "on duty". The analysis techniques discussed in section 2.1.3 are invaluable, yet, some equipment always seems determined to prove that statistics are only averages [6] or even best guesses. This equipment seems to test the validity of the statistics in which the analysis tools are based. This raises questions about the underlying assumptions made for each statistical tool, the methods of recording data for analysis, and even specific fault-finding methodologies.

2.2.1 Analysis & Assumptions

The promise of modern statistics is that it provides not only a precise summary of the conclusions drawn from an evaluation, but also a reliable prediction for future tests [14]. It is, of course, impossible for statistics to prove that something is true; only that the preponderance of data support that conclusion [29]. As with any model,

calculated assumptions must be made to either simplify the problem and/or fill in the unknown characteristics of a phenomena. It can be expected, to a minimum degree hopefully, that actual behavior will not follow the predicted statistical model accurately for a given period of the life cycle. The causes behind this variance can be attributed to poor assumptions due to either lack of pertinent information or lack of understanding of statistical processes, or both.

2.2.1.1 Lack of information

Statistical analysis is not new. It has been applied to a wide variety of engineering problems since the early 1970's. Methods employed were studied up to 200 years ago like the Guassian distribution, named after Karl Guass, more readily known as the normal distribution which adequately describes many mechanical components[2]. Another popular technique was proposed by Waloddi Weibull in 1951 and is known as the Weibull distribution -- highly acclaimed for its simplicity and versatility. The log-normal distribution is also sometimes used to model system behavior since in many applications, especially RAM, the data may not fit the normal distribution. Figure 5 shows that the three distributions have similar behavior near the center, but very different behavior near the "tails" [2].

Techniques for determining which curve is a best fit for particular sample data can be little more than guess work since the probability of a sample lying in the center portion of the curve (the mean plus or minus two standard deviations) is 95.45 percent [14]. Since many engineering risk assessments quote a "six nine" (0.999999) reliability based on a confidence level that *assumes* the form of the underlying population distribution level is known, applying the wrong distribution will prove the "six nine" reliability a gross exaggeration. Thus, the choice of a wrong distribution could result in an overestimation of structural reliability or the calculating of an unrealistically high potential for disaster [2] -- both compounding the problem of diagnosability.

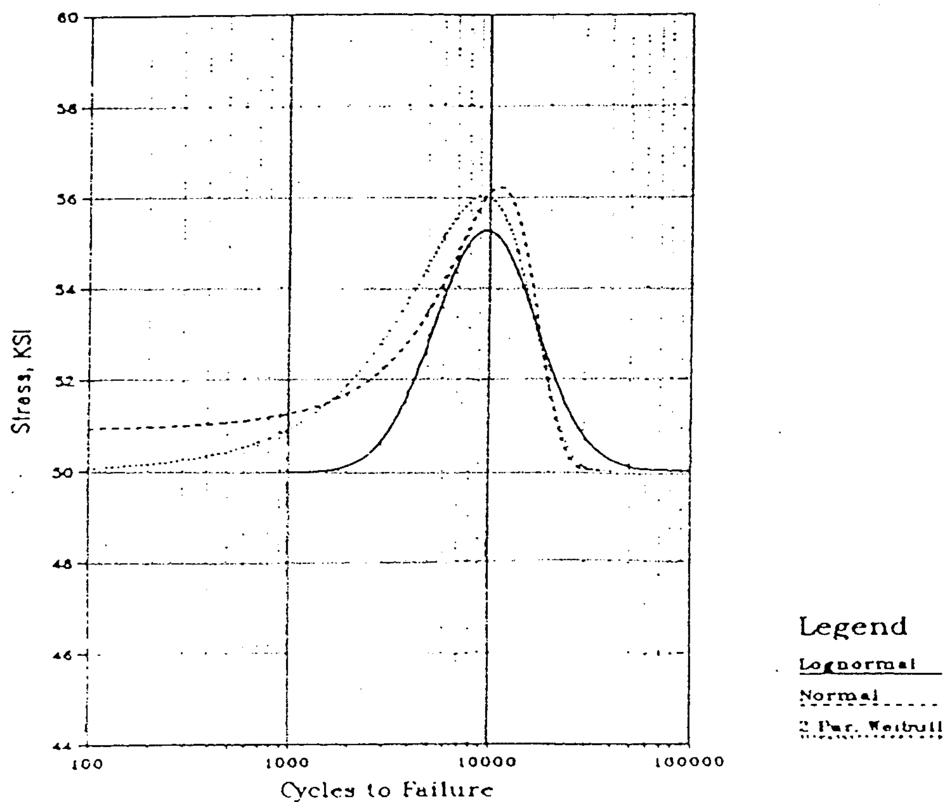


Figure 5. Lognormal, normal, and Weibull distributions [2]

Another source of error due to lack of information is unanticipated potential failure modes. The historical account of an Eastern Airlines flight illustrates this error graphically:

> On May 5, 1983, as an Eastern Airlines L-1011 began its decent into Nassau following a 47 minute flight from Miami, the No. 2 engine was shut down because of low oil pressure. After turning to head for Eastern's maintenance base in Miami, the No. 3 engine failed, followed shortly by the No. 1 engine. The L-1011 had experienced a *triple* engine failure!" [2]. Fortunately there was a happy ending. The No. 2 engine was restarted at an altitude of 3,500 feet and the plane made a successful landing in Miami [2].

Failure of a single engine is unusual, failure of two is even more unexpected, and the probability of all three failing should be infinitesimally small -- or, was the probability grossly underestimated? The National Transportation and Safety Board determined the triple engine failure occurred because all three engines had magnetic

chip detectors installed without "O" ring seals. Loss of oil caused the engines to overheat and stop running. All three were installed on the same night, by the same two-man team on a late-night shift under poor lighting conditions. Thus, the probability of installing three incorrectly, in this case, was the same as the probability of installing one incorrectly. The omission of an "O" ring seal was unanticipated and would likely not have been included in a prior risk assessment or diagnosability target [2].

2.2.1.2 Lack of Understanding

Some misconceptions are difficult to avoid as can be illustrated with the previous example. For instance, incorrectly applying the rules of probability could easily result in an overestimated reliability. The probability of the failure of all three engines on the same flight would likely have been incorrectly computed by "multiplying probabilities" of individual failures, *assuming* independence [2]. This assumption had devastating results. Difficulties like these make probabilistic life analysis and diagnosability alluringly simple in principle, yet unfortunately vulnerable to misuse and error.

Minimization of misconceptions about statistical probabilities can be easily accomplished with some study and application. Many misconceptions are due to misleading terminology such as "bathtub curve" and "failure rate".

Reliability can also be expressed in the mathematical terms:

$$R = e^{-\lambda t} \tag{9}$$

Where R is the probability of the item completing the specified mission successfully, e is the natural logarithmic base, t is the duration of the mission, and λ is the failure rate of the item throughout the period [21]. A special case of the Weibull distribution, equation 9 represents the exponential distribution. Acceptance of this equation presupposes a subordinate *assumption* that failure rate (λ) is constant over the

product's entire operating life cycle. Testing and experience have proven that failure rate versus life cycle more closely approximates a "bathtub curve" which can model the reliability characteristic of a generic piece-part type, but not of an entire system which some analysts profess. Even if an exponential distribution is assumed, as often is the case for electrical and some mechanical parts, the reliability bathtub curves show the useful life can vary extensively from the statistical assumption (see figure 6).

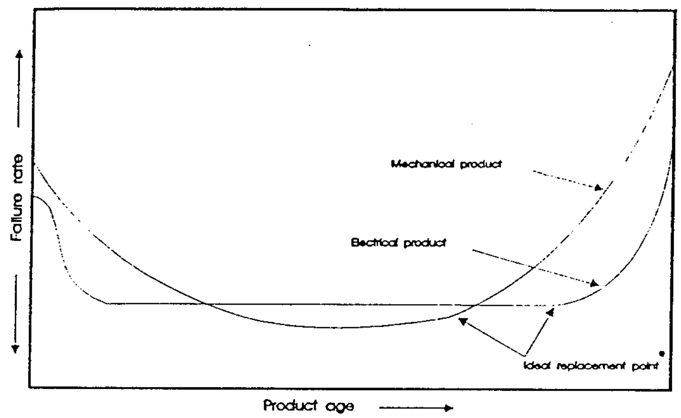


Figure 6. Bathtub curves for electrical vs. mechanical parts [7]

Additional considerations often neglected for this statistical model include changing environmental stresses, variations in tooling, and other manufacturing influences. Thus, instead of a simple curve, the reliability might be better depicted with these factors in mind as shown in figure 7.

Furthermore, most analysts do not realize that *the* bathtub curve is applied to both repairable and nonrepairable systems. This assumption implying that the Force of mortality (FOM) for parts and the rate of occurrence of failures (ROCOF) or failure rate for a repairable system are equivalent is terribly wrong [3]. Therefore, two bathtub curves should be represented as shown in figures 8 and 9.

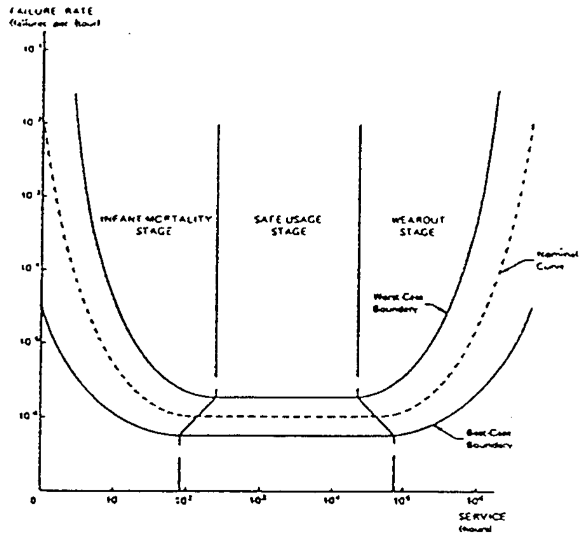


Figure 7. Bathtub curve reflecting environmental and manufacturing stresses [21]

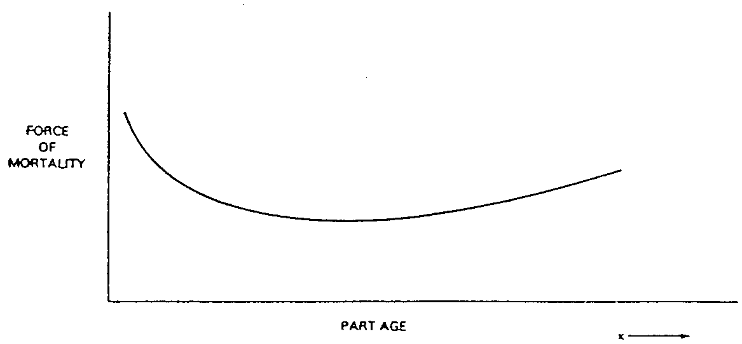


Figure 8. Bathtub curve for parts [3]

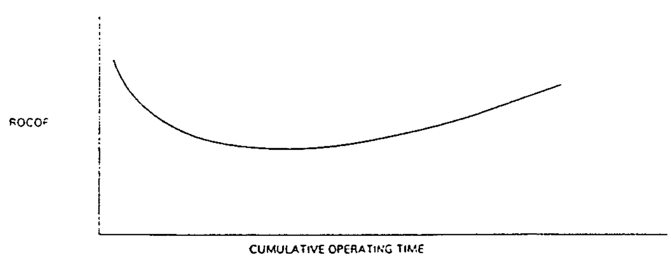


Figure 9. Bathtub curve for a repairable system [3]

Other false assumptions due to lack of understanding include, but are not limited to: assuming a linear plot of failures versus time on linear paper implies a

homogeneous Poisson Process; reordering data with respect to magnitude instead of chronological order; assuming overhauls are equivalent to renewals; and, confusing "reliability with repair" for repairable systems [3]. All, either directly or indirectly, affect system diagnosability by introducing errors to the system model.

Since the process of probabilistic analysis has been introduced considering statistical distributions of all (known) contributing factors, the key question remains -- "What constitutes acceptable risk?". Considering the possible errors in risk assessment, the pilots of the Eastern L-1011 would likely say the "six nine" reliability was *not* acceptable. However, this is the risk that they (unknowingly?) accept every time they climb into an aircraft [29].

2.2.2 Analysis & Recording Data

Data used for analysis can be obtained either from tests on prototype or production models or from the field. In either case, some means of accurate recording of this data must be available or errors will result in analysis conclusions. Most methods of recording data involve human interface with extensive forms such as the reliability centered maintenance form located in appendix A. Since the data acquisition depends on persons rather than equipment, errors often occur due to omissions and misinterpretations which can be traced back to motivation, training, and diagnosability.

If the maintenance technician can see no purpose in recording the information, especially under poor working conditions, it is likely that items will be omitted or recorded wrong. Once a failure report has left the initial recorder the possibility of verification is very much reduced, especially due to the high cost of man-hours. These conditions increase the probability of recording a failure when no failure exists (a non-failure). The testing and replacing of no-fault items or LRUs because of convenience or previous experience is a likely cause for this. Also, when multiple faults occur, a technician may record a secondary failure as a primary failure. All of these errors in recording cause artificial inflation of failure rate data. Training and

motivation through knowledge can inhibit these errors immensely, yet can never totally remove incidents of incorrect failure recording [4]. Improved diagnosability can limit, if not eliminate, replacing no-fault items as well as chronological recording errors.

2.2.3 Analysis & Methodologies

Several popular diagnostic analysis testing techniques have emerged based on particular environments. Especially with the advent of the digital computer, these techniques have reduced many sources of error, but are not totally without disadvantages. To minimize errors, testing needs to follow certain methodologies as well as use the best analysis equipment for the particular application.

2.2.3.1 Testing procedure

Several papers have been written addressing the subject of element, or LRU, checking order. With optimality based on cost, all analyses converge on the following general principle: check first the LRU that minimizes

$$\tau q/p \tag{10}$$

where τ is the testing cost, q is the probability that the LRU is good, and p is the probability that the LRU is bad [30]. Using this procedure can optimize diagnosability, yet, once again, statistics are only averages based on historical data at best.

Simulated natural and induced environmental tests have been developed scientifically or through trial and error to provide laboratory conditions comparable to actual field test conditions if field data is not available. The procedure for diagnostics remains the same for both conditions, yet checklists have been developed to specify and calibrate the transducers used and minimize unwanted "noise" in the test environment.

Checklists have been developed for several diagnostic tests including

temperature, humidity, mechanical shock, vibration, sunshine, dust, rain, and explosive environments. For example, the checklist of specification considerations for a temperature test include: the test temperatures and their tolerances; exposure time and its tolerance (10% of duration recommended); protection against moisture condensation and frost; functionality desired; relative humidity; the number of sensors and their locations; and, the initial temperature of the product at the start of the test [14].

The transducers used for instrumentation in the tests need to be considered according to the specifications required. For instance, the decision to use a piezoelectric instead of a strain gauge accelerometer for a mechanical shock test involves required specifications such as sensitivity, linearity, and frequency response.

2.2.3.2 Testing equipment

The actual diagnostic equipment used today has been greatly influenced by the evolution of the digital computer to keep up with the advances of the products they are diagnosing. The advent of analysis techniques such as the FFT (fast Fourier transform) have also revolutionized diagnosability as well as BITE (built in test equipment) technology. An example lies in the arena of rotating machinery, but can be applied to any system. Traditionally, vibration monitoring and protection equipment has been totally separate from the diagnostic and data acquisition equipment. Multiple microprocessors now virtually eliminate this barrier and can answer diagnostic questions in "real time". Questions include: is the data believable? to what accuracy?; can I continue to run the machine? for how long? at what speed?; what happened to the machine?; when, where, and how did the malfunction occur?; for how long did it last?; what was the sequence and correlation of events?; what is the past history?; what limits were exceeded?; and, who can help? To answer these questions microprocessors calculate peak-to-peak vibration and display it on bar graphs, perform DFT (discrete Fourier transform), compare vibrations against stored alarm limits, trip defeat functions for calibration and maintenance, calculate time to danger, measure transducer gap

voltages, perform self tests, and produce buffered output for test instruments. This is all accomplished because of microprocessor's enhanced speed due to: parallel channel monitoring; positive capture since connection is permanent; additional data availability such as time to danger; flexibility due to programming for different functions; reliability since downstream failures do not impact upstream functions; compatibility from the digital form of data; and, self testing capabilities [15].

With the discovery of the FFT (fast Fourier transform), process time for time to frequency transformations has been exponentially diminished so "real time" diagnosis of systems can be accomplished. Amplification of defects in rotational machinery is possible using the FFT on a logarithmic scale or cepstrum analysis (a variant of the FFT). These discoveries allow tracking of extremely slow changes in the transfer function such as crack growth development [25]. A typical frequency-based troubleshooting checklist is located in appendix A.

Malfunctions, such as bearing deterioration, can be discovered using various equipment with advantages and disadvantages influencing error and cost for each. For instance, if the human ear is the only diagnostic source for detecting a malfunction, the time to failure will likely be rather short, but the cost of equipment will be quite small. If a stethoscope is added, the costs rise to approximately $300, but detection is sooner. The errors involved in any sound method include subjectivity, inaccuracy in trend analysis because of no hard copy readings, and lack of severity detection. Temperature methods, such as portable pyrometers or permanently installed thermocouples, are relatively inexpensive, but the detection is often too late to replace the malfunctioning part during scheduled downtime and the analysis is often in error since temperature varies with load. Vibration methods are generally very expensive (real time analyzers start at $8500) yet have a proven track record of early detection if used properly (see figure A2 in the appendix). Lack of training can result in error with the vibration method [4]. Still other methods include ultrasonic, shock pulse, spike energy, acoustic emission, and fiber optics -- each with probable sources of error and definite application strengths.

In order to prevent systems from proving that statistics are only averages and failing when "on duty", choices are available to minimize the potential for error through diagnosability. Assumptions in statistical methods, recording techniques, and methodologies including testing and equipment are all variables to optimize.

2.3 Diagnosability & Design

Diagnostic equipment and tools available today, in general, are limited to after-the-design add-ons like BITE technology (which add weight and volume) or maintenance personnel tools (which many times require system shutdown for analysis). Since the quality of a product is determined, to a great extent, during the design phase rather than during production [11] and if both cost and analysis are functions of diagnosability, design techniques should be explored to maximize the diagnosability inherent in the product -- keeping add-on diagnostic systems to a minimum.

2.3.1 Traditional Design

The cost of the unjustifiable removals on the 747 noted earlier was $100 per flight hour, "a cost equivalent to adding 8 tons of dead weight to the aircraft," directly attributed to poor diagnosability with respect to the components that were removed [11]. Traditional diagnosability has been an afterthought of product development.

Problems in both electronic and mechanical systems are addressed by adding sensor based systems such as automatic test equipment (ATE) and BITE [11]. These require communication devices called networks as a means for telemetry to correlate and analyze data for diagnostics from various different parts of the system where "smart sensors", like those discussed in section 2.2.3, monitor target parameters. These add-ons not only add weight and volume (severely detrimental to businesses like

Boeing), but complexity as well -- likely reducing reliability due to the diagnosability equipment itself failing.

Another common approach, used alone or in conjunction with add-on equipment, is removing and servicing equipment on a cyclical basis based on mean time between failures and other trend analysis statistics [6].

One reason fault diagnosis is not considered explicitly until late in the production process is that diagnosability is difficult for the designer to consider without actual maintenance data [11]. Certainly, there must be some way to design for reliability through diagnosability without overdesigning as with the historically noted One-Hoss-Shay.

2.3.2 Diagnosability Factors in Design

Several factors can be used to compare competing designs with respect to diagnosability and decide what parts of a system could be improved in the design phase. Included in theses factors are the placement of parts based on function (and reliability if known), the placement and choice of sensors, and the redundancy of sensing operations and LRUs.

Based on equation (8) of section 2.1.2, diagnosability time is directly proportional to the time until initial detection, the average number of candidates for a given failure, and the distinguishability between the candidates. The time until initial detection is a function of the detection equipment of the particular LRU and can be modified using techniques discussed in section 2.2.3 based on the criticality of the part and its probability of failure.

From previous work (Clark, 1993) the average number of candidates for a given failure can be expressed as

$$\bar{c} = (1/n)\sum_{i=1}^{n} c_i \tag{11}$$

where c_i is the number of candidates for each failure indication, i, summed over the total number of different failure indications, n [11]. It has been said that the maximum number of candidates for a particular failure is a measure of the ambiguity of a system, so LRUs with a high $\bar{c}$ may confound diagnosis -- especially if the same LRUs have a high probability of failure. Decreasing $\bar{c}$ can be accomplished by placing particular units in different locations or changing sensor dependencies.

The measure of distinguishability can be expressed as

$$D = \frac{\sum_{i=1}^{n} (1/c_i - 1/c)}{n(1 - 1/c)} \tag{12}$$

where n is the total number of possible indicated failures, c is the total number of candidates in the system, and c_i is the number of candidates for each failure, i [11]. This equation shows that a distinguishability of one, or 100%, means that every possible indicated failure would have only one candidate and diagnosis is trivial, where as a distinguishability of zero means that for any failure, all LRUs in a system are candidates, i.e., poor diagnosability [11]. Improving D can be accomplished by, once again, decreasing the total number of candidates and/or decreasing the complexity of the total system.

A popularized factor for increasing the reliability of a system is the use of parallel linked redundancy of LRUs versus series linked components. By inspection, systems with LRUs linked in series have a failure rate equal to the sum of the failure rates of each LRU. Parallel linked systems decrease the failure rate. For example, the mean time between failures for an equivalent system with two LRUs in parallel can be expressed as

$$\frac{1}{\lambda} = \frac{1}{\lambda_1} + \frac{1}{\lambda_2} - \frac{1}{\lambda_1 + \lambda_2} \tag{13}$$

If the failure rates of the two components are equal, equation (13) reduces to $\frac{3}{2}\theta$, where θ is the mean time between failures of each LRU [21]. Figures 10 and 11 show the relationships for series and parallel systems, respectively.

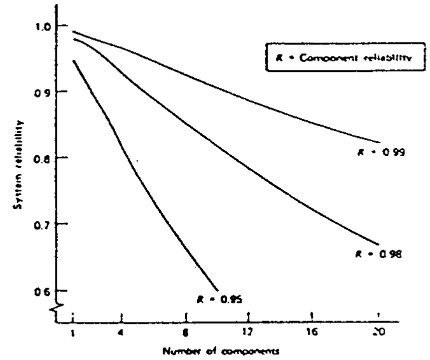


Figure 10. Series system reliability [18]

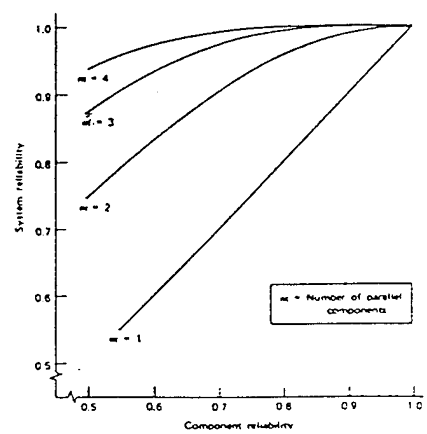


Figure 11. Parallel system reliability [18]

However, improving reliability through redundancy is a method subject to restrictions. In electrical *and* mechanical systems the performance parameters of a combination of LRUS is not the same as for the original component alone and the degraded performance of the system after one LRU fails is likely to be less than the parallel combination. It should be emphasized again that redundancy reliability, like BITE, carries the penalty of added space, weight, power supply, and cost as well as the possibility of more maintenance activities.

Efforts to enhance reliability through complexity quickly reach a point of diminishing returns from the diagnosability point of view.

The previous considerations for improvement have been limited by the functionality requirements of the system as well as the other factors in design. If a system *must* be configured in such a way that changing LRU positions is impossible, then placement and type of sensor associated with each LRU function can be optimized in lieu of merely adding sensors (and weight and complexity). One study utilizes the minimization of a positive definite scalar measure of the covariance matrix as an optimality criterion for sensor locations based on minimizing sensor uncertainties [26]. The idea of "smart sensors" implies the sensor, along with a microprocessor, makes the diagnostic decisions itself [6]. Of course, the weight and volume capacity of the system and LRU may determine just how "smart" a sensor can be.

Sensor placement can also be a factor of interfering inputs. External or internal "noise" associated with system operating conditions can contribute to false out-of-tolerance readings or mask true out-of-tolerance signals. This phenomena increases either unjustifiable removals or allows for LRU failure without prior notice, respectively. Placement for minimum interference or use of filters to eliminate excess noise can increase diagnosability without additional complexity.

2.3.3 Design for Diagnosability

While some systems incorporate microprocessors programmed to test and isolate faulty LRUS and even switch to backup devices, most require fault isolation provisions like accessible probes or connectors called test points. Test points provide an interface between test equipment and the system for the purpose of diagnosis, adjustment, and monitoring of performance. The provision of test points is governed by the level of LRU chosen and will usually not extend beyond what is required to isolate the particular faulty LRU [4].

2.3.3.1 Testability

To minimize the possibility of faults being caused by maintenance activities, test points must be in standardized positions within the circuit buffered by capacitors and resistors to protect the system from misuse of test equipment. Enough space should be provided to allow for test probes of the test equipment. As with BITE, reliability of the test equipment should be an order of magnitude better than the system. Additional strategies to assess design effectiveness for testability can be found in Mil-Std-2165 [24]. The standardization of probes reduces the amount of test equipment as well as lessens the probability of having the wrong test gear. It should be noted that additional unnecessary test points are likely to impair rather than improve system diagnosability and therefore must be chosen carefully in the design phase.

2.3.3.2 Ease of maintenance

Several design considerations can ease maintenance actions and improve diagnosability. First, if at all possible, minimize maintenance in the first place. For example, development of electronic fuel injection in automobiles has eliminated the need to check the distributor condition [24].

Many additional items, similar to DFA (design for assembly) goals, reflect the human factor.

Accessibility refers to fasteners and covers as well as position of mounting relative to other parts. Parts should be easily removable with features such as quick disconnect plugs for hydraulic and electrical parts, yet technicians should be discouraged from removing and checking easily exchanged items as a substitute for the correct diagnostic procedure. This can be accomplished by the choice of connections of the particular LRU, which presents the classic trade-off between reliability and maintainability. A high reliability LRU which is unlikely to require replacement could

be connected by a wrapped joint, whereas a low reliability LRU could be connected by a less reliable plug and socket for quick exchange [4].

The amount of adjustment required during diagnosis can be minimized by generous tolerancing during the design. Guide holes for adjustment tools and visible displays are also helpful for avoiding damage to the equipment and monitoring adjustment levels, respectively [4].

Design for off-line repair can increase the use of spares, but decreases downtime immensely. Considerations here include the handling capacity and size of the LRU. Good handling requires lightweight parts with handles to avoid equipment damage as well as protect from sharp edges and high voltage sources (even an unplugged module can hold dangerous charges on capacitors) [4]. Generally, as the size of the LRU increases the reliability decreases and the cost of spares increases.

Several ergonomic factors influence diagnosability based on performance aids and the environment. Since the short term memory of a human has the capacity of only about 7 bits of information, designs should require minimum tests for diagnosis and minimum skill [11]. Overminiaturization should be avoided if possible. Environmental conditions such as illumination, comfort, and safety in the form of body positions and stress generating factors like weather, heat, vibration, and noise should all be an integral part of design considerations [4]. Figure 12 illustrates how stressors such as temperature can affect diagnosability.

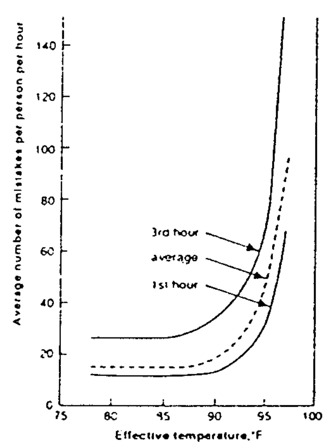


Figure 12. Effect of temperature on number of mistakes [24]

A complete checklist of diagnosability design with respect to human factors can be found in reference 31.

2.3.4 Selection of Designs

Design selection, from the earliest stages of concept development, should consider every slice of diagnosability improvement introduced in the previous sections. From the LRU to the entire system configuration, selection of particular designs can be optimized using techniques involving life cycle costing based on historical and predicted data, mathematical prediction models based on advances in diagnosability technology, and screening methods using prototype or production parts.

As noted previously, life cycle costing provides essential comparisons between existing system architectures based on historical field data and design phase concepts based on prediction techniques. Using cost of diagnosability as the common metric, the optimal system design can be chosen from a set of limited choices.

Mathematical prediction models are used extensively to weigh the savings of discrete advances in diagnosability technology. For instance, one study developed a mathematical model for predicting impact on maintenance man-hours of on-board test equipment in the form of BITE for use in the conceptual design of aircraft including the USAF Advanced Tactical Fighter (ATF) [17]. The cost and performance penalty of incorporating BITE must be balanced or exceeded by cost savings in support, manpower, and improvements in availability to justify incorporating this technology in the design. The life cycle costing mechanism available through the Boeing Company is called the DEPCOST (dependability cost) model. This model, available for use on the spreadsheet program Excel 4.0 or higher, incorporates all parameters that affect the cost of an aircraft throughout its 20 year life cycle.

If actual products are available for testing, screening based on reliability and diagnosability parameters can be accomplished using several techniques including: screening by truncation of distribution tails based on tolerance limits defined by a

normal distribution; "interference" between stress and strength distributions, again using normal distributions of environmental stress and product strength to eliminate products where intersections occur; burn-in screening to identify and eliminate products with early failure mechanisms; and, linear screening which predicts early failures based on a weighted average of early life parameters.

Selection of designs based on diagnosability promises to move today's products from weighty/costly add-ons to maintenance-friendly/efficient machines with diminishing costs.

3.0 DESCRIPTION AND MODELING OF THE BOEING 737-300 BLEED AIR CONTROL SYSTEM

This section introduces the bleed air control system (BACS) including major LRUs and their indications. The scope of the analysis and all assumptions are explicitly stated for the system. Modeling of the system is accomplished with the use of a failure modes and effects analysis (FMEA) by Airesearch and maintenance manuals provided by the Boeing Company. Failure combinations are incorporated in similar fashion to previous research (Clark,1993) for ease of comparison analysis and application of system metrics. Though the 737-300 is singled out in this research, all analyses and recommendations can be extended to the 400 and 500 models since they are exactly the same.

3.1 Description of the Bleed Air Control System (BACS)

The BACS consists of two identical sets (one per engine) of valves, controls, ducts, and a heat exchanger mounted in the engine nacelle area as shown in figures 13 and 14.

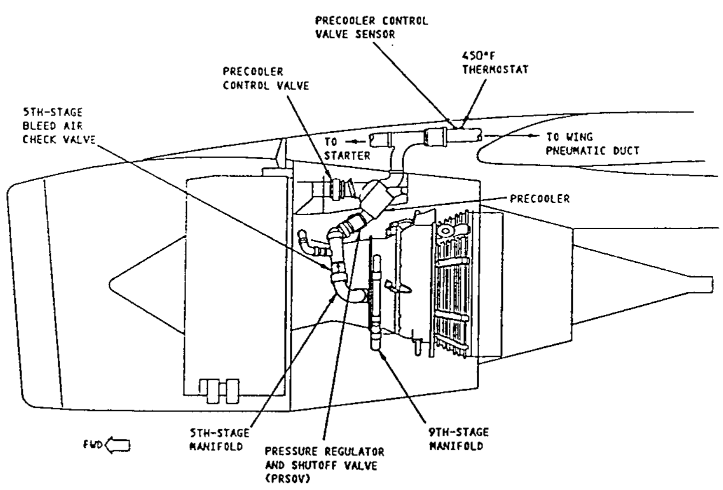


Figure 13. 737-300 BACS component location - left view

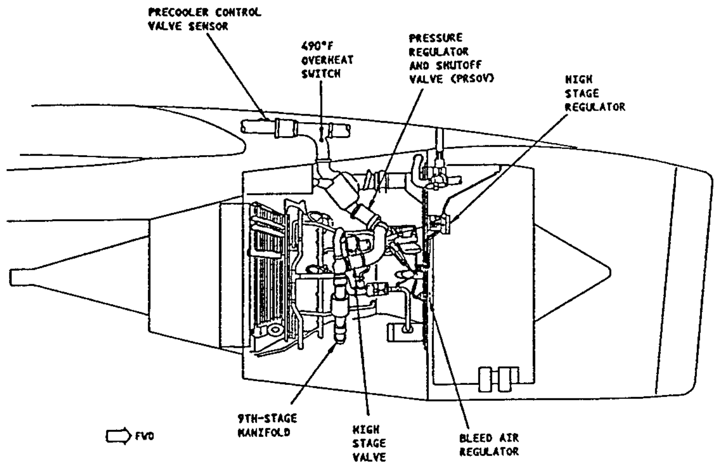


Figure 14. 737-300 BACS component location - right view

Each set of equipment automatically selects the engine bleed air supply from either the low-stage (5th stage) or high-stage (9th stage) bleed ports and regulates the pressure and temperature supplied to the air-using systems such as cabin air conditioning, cargo heating, and anti-ice.

Bleed air from the 5th and 9th stage compressors is routed through a heat exchanger, called the precooler, where it is cooled with air from the engine's fan. From the precooler, the air continues to the pneumatic manifold as shown in figure 15.

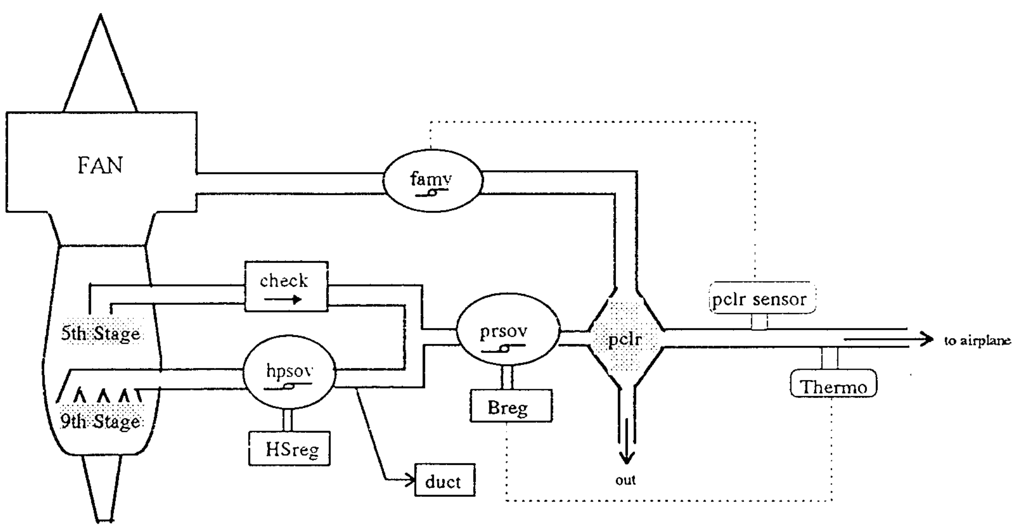


Figure 15. 737-300 BACS schematic

Since bleed air must be delivered to the pneumatic manifold within specific temperature and pressure ranges to prevent under/overheat and under/overpressure conditions, a number of valve and control systems are used for regulation.

During takeoff, climb, and most cruise and hold conditions, the pressure available from the 5th stage is adequate to meet the requirements of air supply used. During descent, approach, landing and taxi conditions 9th stage bleed air is required. The selection of the bleed supply is controlled by the high-stage valve (HPSOV) and the high-stage regulator (HSreg) setting. The HPSOV is responsible for regulating and shutting off the flow of 9th stage engine bleed air in conjunction with signals from the remotely located HSreg which selects the proper bleed air stage as necessary to satisfy system requirements. The low pressure check valve (Check) permits the flow of 5th stage bleed air and prevents higher pressure air from the 9th stage from back flowing into the 5th stage. The pressure regulator and shutoff valve (PRSOV) limits bleed air to a predetermined pressure level for the system. Secondarily, the PRSOV works in conjunction with the 450°F thermostat (Thermo) as a flow modulating valve to limit downstream temperature within a maximum upper temperature band based on signals from the Thermo. A remotely located bleed air regulator (Breg) works with the PRSOV to control the output pressure to a maximum and incorporates an overpressure switch which activates the PRSOV to close in the event of extreme bleed pressure. The precooler control valve (FAMV) controls the flow of fan cooling air to the bleed air precooler (PCLR). The FAMV modulates in response to pneumatic control pressure signals from a remotely located precooler control valve sensor (PCLRsen) to maintain bleed air temperature downstream of the precooler within a specified range. The PCLR vents excess air to ambient as do the HPSOV and PRSOV by incorporating pressure relief valves to provide additional actuator relief in the event of transient overshoots. All components are connected by a series of ducts (duct).

The BACS currently has five sensors, or indications, that are used to diagnose system failures. These indications include 1) above normal readings on an analog pressure gauge 2) below normal readings on an analog pressure gauge 3) bleed trip off

light illumination 4) low cabin pressure on an analog pressure gauge, and 5) low cabin temperature on an analog temperature gauge. All subsequent analysis refer to these indications in the predeeding numerical order, e.g., bleed pressure hi & bleed trip off equals indication 13.

3.2 Scope and Assumptions of BACS Analysis

3.2.1 Scope

The valves, controls, ducts, and systems making up the BACS and described in the previous section (parenthetically denoted) are considered LRUs which can be replaced on the repair line as the lowest physical level of replacement. Each LRU provides a function for the system that can be measured. The five indications listed provide the performance measures of each LRU individually and collectively depending on the mode of operation of the system. An example is the HPSOV providing pressure to the system measured by the analog pressure gauge on the pilot's overhead panel. The LRU, HPSOV in this case, is directly associated with an indication, pressure in this case. The LRU to indication relationship is causal in direction.

Each indication, though, does not necessarily imply a causal relationship to an LRU unless only one LRU could have possibly caused the indication--a distinguishability of one (section 2.3.2). The process of diagnosis is one of determining the set of parameters,or LRUs, of a system that have parameter measures, or indications, that fall outside the desired (or necessary) design values. This indication to LRU relationship is diagnostic in direction, and the resulting set of suspect LRUs are called candidates [11].

The scope of BACS model is to define the LRU/indication relationships in such a way as to incorporate all LRUs and indications in the system as well as all modes of failure of each LRU. Successful completion of the model allows for systematic

changes to be incorporated and analyzed. Assumptions are made to simplify the analysis and to provide consistency with a real system.

3.2.2 Assumptions

As opposed to previous research, this analysis incorporates all operating conditions of the aircraft at once since the information from all engine output conditions is realistically available to maintenance personnel. To move beyond the trivial, proper electrical power is assumed to be available to the system, a failure that has no indication associated with it is not considered, and an indicator failure is not considered since the flight crew can establish its validity. Failure of circuit protection is not considered. Valve port leakage and external leakage are not considered.

Only one LRU failure at a time is considered, i.e., mutually exclusive, though an analysis technique for dependent LRU failures (passive) is developed. All ducting is considered to be one LRU. The failure rates experienced based on the FMEA and Boeing's Dependability Cost (DEPCOST) model are in the same proportion as those predicted. Failure modes obtained from the FMEA for the BACS are the only failure modes considered. Maintenance is performed in accordance with established maintenance procedures and by personnel possessing appropriate skills and training.

Inputs to the BACS model are obtained through design standards and engineering judgment if not stated explicitly by the Airesearch FMEA or Boeing publications.

3.3 Modeling of the Bleed Air Control System (BACS)

Failure mode information is available from the FMEA conducted on the 737-300 BACS including probability assessments for each mode of failure. Mean time between failures for each LRU is available from a completed DEPCOST model based

on historical data and maintenance reviews for the system as well. Since an LRU can fail in several ways, a "sometimes" indication developed to exhibit relations between failures and indications that only sometimes promote failure indications. The fault tree analysis model of the BACS shown in figure 16 incorporates both always and sometimes relations depicted as solid and dashed lines, respectively. Due to space constraints the LRU failures (rectangles) are placed both above and below the indications (ovals).

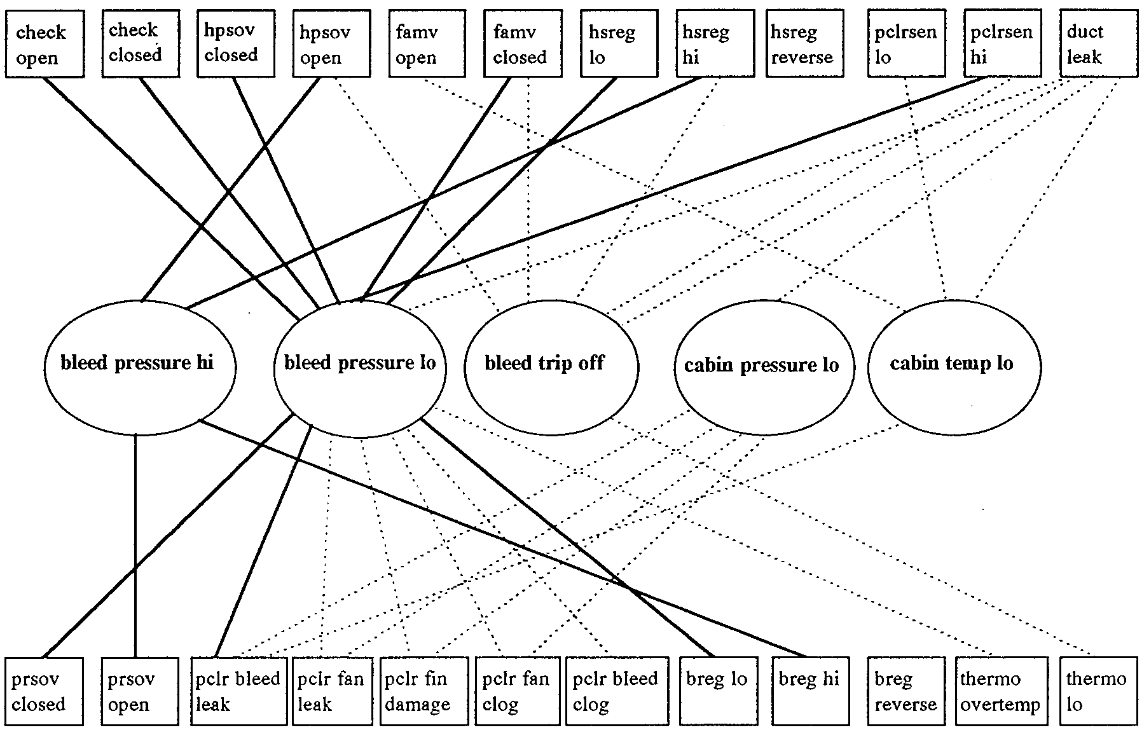


Figure 16. Fault tree analysis model for the BACS

With this defined system model, metrics can be developed to compare different systems that perform the same function by totally different designs or by reassigning LRU-indication relationships. Refining previous research metrics (Clark,1993) to address dependent/passive failures and defining a prediction method to determine mean time between unscheduled removals (MTBUR) leads to a redesign methodology based on diagnosability. Incorporating these prediction metrics into the life cycle costing mechanism DEPCOST model, total diagnosability cost savings can be discovered.

4.0 DIAGNOSABILITY METRICS AND REDESIGN METHODOLOGY

For diagnosability to be considered in the design/redesign process, there must be some way to predict how system changes will affect system parameters for comparing competing designs with respect to diagnosability. A methodology based on the prediction technique must be arrived at for use in determining what parts of the system should be changed to improve diagnosability. In section 4.1, metrics from previous work are extended to measure the relative diagnosability of systems with LRU failures that are dependent/passive. A prediction metric based on unjustified removals and time is introduced in section 4.2. A design change methodology is discussed in section 4.3.

4.1 Dependent Failures

As noted from previous work (Clark, 1993), determining which LRUs are difficult to diagnose is not complex. By examining the fault tree analysis model of figure 16, a list of all possible failures and their corresponding candidates can be assembled. It may seem that the greater number of times a certain LRU appears as a candidate, the harder it is to diagnose. Yet, if that particular candidate is the only candidate for many of its failure modes it does not present a diagnostic challenge at all. Moreover, even if a certain LRU is hard to diagnose, it may be of little concern if its failure is very unlikely to occur [11].

Taking the above factors into consideration, equation 12 of section 2.3.2 was modified to reflect the probability, or failure rate, of each particular LRU as shown in equation 14 as weighted distinguishability [11].

$$WD = \frac{\sum_{i=1}^{n}\left\{PF_i\left(1/C_i - 1/C\right)\right\}}{\left(1-1/C\right)\sum_{i=1}^{n} PF_i} \tag{14}$$

PF_i is the probability of LRU failure as defined by equation 15.

$$PF_i = 1 - \prod_{candidates}\left(1 - PC_j\right) \tag{15}$$

PC_j is the probability of failure of each of the candidate LRUs for a given indication. Weighted distinguishability, like distinguishability, varies from zero to one, but provides a more realistic approach to system diagnosis comparisons.

Metrics defined up to this point have been derived from a mutually exclusive standpoint with respect to failures, i.e., only one LRU failure occurs at a time to produce a given failure indication. Realistically, this is not always the case. In fact, the 737-300 FMEA incorporates a section of passive LRU failures, that, in conjunction with certain other passive failures, activate a failure indication -- therefore the LRU failures are dependent.

Since merely the incidence of one passive failure will not generate a failure indication, the definition of PF_i for use in equation 14 should be expanded to incorporate dependent failures such as that depicted in the fault tree analysis model of figure 17 if one or more passive LRU failures are to be modeled.

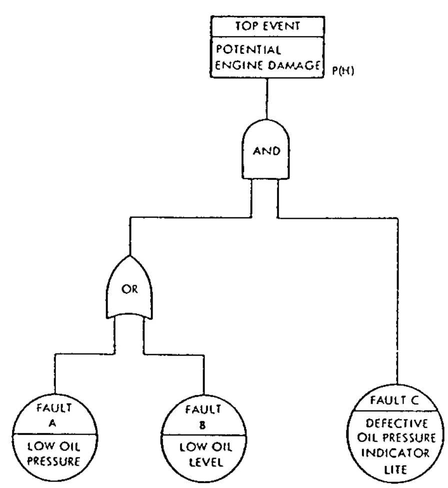


Figure 17. Sample fault tree analysis including independent and dependent sources [10]

Equation 15 essentially defines the additive rule of probability. Incorporating a dependent passive event such as fault C in figure 17 requires the use of the multiplicative rule of probability. For such modeling, equation 16 is suggested for use in equation 14.

$$PF_i = \left[1 - \prod_{candidates} \left(1 - PC_j\right) \prod_{candidates} PC_{k1}\right] \prod_{candidates} PC_{k2} \tag{16}$$

Once again, all PC terms are the probability of failures of each of the candidate LRUs for a given indication, yet based on dependency. PC_j is independent, PC_{k1} has an "embedded" dependency, and PC_{k2} has an "extended" dependency. Figure 17 models an extended dependency of fault C. Though, if the "and" and "or" gates were switched, the dependency would be embedded between faults A and B. Of course, the PC_k terms are only utilized if the model embodies them, otherwise they are discarded and equation 15 suffices.

Though the analysis of the passive failures in the 737 BACS system is not included in the scope of this research, weighted distinguishability can now be applied to virtually any system modeled by fault tree analysis.

4.2 Mean Time Between Unscheduled Removals (MTBUR)

Attributed by Boeing as the "single most important input" in the DEPCOST model, MTBUR has been targeted by this research as the overriding prediction parameter of diagnosability. For an aircraft system, MTBUR is defined as the average number of unit flight hours occurring between unscheduled removals of an LRU. Mathematically, it is the inverse of the LRU removal rate. Reliability mathematics and labor time are the key contributors to the derivation of the predicted MTBUR based on LRU failure rates and system structure.

Though the normal distribution is capable of describing most mechanical part lives, the scheduled maintenance overhaul and replacement times are assumed to be within the middle portion of the curves shown in figure 6 of section 2.2.1. Therefore, the exponential distribution of equation 9 is used in all subsequent analysis--assuming a constant, or near constant, failure rate. The structure of a system is most readily evaluated in terms of times to complete maintenance actions. The assumption of constant working conditions in the context of human factors as well as proper experience and training are made. Equation 2 is used to define mean time between failures (MTBF) to avoid redundancy in the calculations by accounting for existent false alarms. The analysis also assumes a certain degree of maintenance technician knowledge prior to diagnosis based on the principle of optimum checking order (equation 10). In this case the cost factor is in the form of line labor hours.

From a generic FMEA a fault tree analysis model can be assembled to include the failure rate of not only the LRU, but also the mode in which it fails. Therefore, a particular failure indication rate can be assessed by summing the failure rates of all LRUs with a common indication:

$$\sum_{i=1}^{n} failrateLRU_i \big| ind_j = failrateind_j \tag{17}$$

given ind_j is the common indication. Since maintenance technicians work in the diagnostic direction, this indication failure rate is a necessary starting point.

In the science of diagnostics an LRU will be removed in one of two conditions: failed or not failed. Removal in the failed condition can be predicted directly from the reliability of the LRU and is justified. Removal in the not failed condition, or unjustified removal, is a function of the probability of detecting the wrong LRU and the time it will take to repair it as well as how often the other LRU candidates for that indication fail. Equation 18 defines the prediction metric for total MTBUR of an LRU.

$$MTBUR_{tot} = 1/\left(1/MTBUR_{un} + 1/MTBUR_J\right) \tag{18}$$

$MTBUR_j$ is the mean time between justified unscheduled removals of an LRU and is equal to the MTBF of that particular LRU. $MTBUR_{un}$ is the mean time between unjustified unscheduled removals defined by the mean time between failures of all other candidate LRUs ($MTBF_{n-i}$)divided by the probability of detecting the particular LRU in question (PD_i):

$$MTBUR_{un} = {MTBF_{n-i}}/{PD_i} \tag{19}$$

where PD_i is defined by

$$PD_i = {PC_i|ind_j}/{(LLHPR + SLHPR)} \tag{20}$$

where $PC_i|ind_j$ is the probability of a particular LRU failing in a mode that incites a given failure indication (generated from $failrateLRU_i|indication_j$), LLHPR is the line labor hours per removal of the particular LRU, and SLHPR is the shop labor hours per removal of the particular LRU. Both time variables are retrieved from maintenance log books and historical data.

For a complete prediction of the total MTBUR of a particular LRU in a system, equation 19 is inverted for each indication to find the unjustified removal rate and then added to the others to find the total unjustified removal rate of the particular LRU. The total unjustified removal rate is then inverted to find the total $MTBUR_{un}$ which is applied to equation 18. Examples of the MTBUR predictions are found in section 5.0 as well as a detailed spreadsheet analysis located in appendix B.

4.3 Design Change Methodology

The MTBUR prediction metric serves as a standard for change when comparing competing designs. Analogous to the Service Modes Analysis (SMA) developed as a

methodology for design changes based on serviceability [12], design/redesign based on the MTBUR prediction metric should focus the following system changes:

1. LRUs with a high λ and low MTBUR.
2. LRUs with high spare costs.
3. LRUs included with highly ambiguous indications (high $\bar{c}$).
4. LRUs with room for improvement ($MTBF - MTBUR \geq 10000hrs$).
5. Candidate combinations that will increase the "overall" system MTBUR, (especially the MTBUR of high cost LRUs)
6. Indications with a high failure rate ($failrateind_j$).

Feasibility of system changes in terms of complexity of LRUs and their functions should also be noted for cost optimality.

The MTBUR prediction metric can be applied to any system with a fully defined fault tree analysis model and design change can be implemented based on the preceding discussion. Diagnosability comparisons and ultimately cost comparisons prove significant gains in insight for analysis based on this technique.

5.0 APPLICATION AND EVALUATION OF MTBUR PREDICTION METRIC

The procedures introduced in the previous sections allow the designer to accurately model an existing system to shed light on which LRUs are a source of diagnosability problems. The designer can also incorporate system changes and see precisely how time and cost are affected. For the BACS, the PRSOV is a known diagnostic challenge due to its historical high rate of unjustifiable removals. Previous work (Clark, 1993) suggests a comparison of metrics such as $\bar{c}$ from equation 11 to identify components, like the PRSOV, with potential diagnosability problems and then an application of equation 14 to find a weighted distinguishability for modified systems to see if an improvement is achieved. Application of the MTBUR prediction metric allows for an immediate evaluation of not only which LRUs pose a threat to diagnosability, but which improvements in diagnosability are feasible.

The current 737 BACS design is the testing ground for the MTBUR prediction metric in section 5.1. Section 5.2 applies the design change suggestions of section 4.3 to develop several redesigns of the system. An evaluation based on MTBUR changes and cost savings is presented along with recommendations in section 5.3. Section 5.4 addresses the issue of spares provisioning.

5.1 Application of MTBUR prediction to the original 737 BACS

As stated earlier, only active/independent failures will be analyzed which make up the vast majority of unjustifiable removals (over 90%). From the fault tree analysis model of figure 16, section 4.2 metrics can be applied for each LRU to arrive at a predicted MTBUR. An example spreadsheet of the original system analysis for the PRSOV is located in appendix B. Using the DEPCOST model for historical values of each LRUs MTBUR, an evaluation of the prediction metric may be accomplished. Table 2 includes values of historical versus predicted MTBUR.

LRU	HISTORICAL	PREDICTED
HPSOV	36018	38931
PRSOV	5394	6789
PCLR	65758	76841
duct	11000	11827
FAMV	16421	27123
CHECK	309102	319140
HSreg	10985	15659
PCLRsen	15168	24106
Breg	11607	16700
Thermo	13799	89645

Table 2. Historical versus predicted MTBUR

Several LRUs (HPSOV, Breg, and duct) had no MTBUR listed. Based on engineering judgment, these LRUs were assigned an MTBUR equal to twice their historical mean time between failures (MTBF). Other omitted items include the SLHPR and spares cost of the Breg and HPSOV which are estimated at values of similar equipment (HSreg and PRSOV values, respectively, varying slightly due to complexity differences). The predicted values fall within approximately twenty percent of the true values with the exception of the 450°F thermostat. This anomaly could be explained by organizational factors outside the scope of this research, e.g., direction from higher levels because of low spares cost, ease of maintenance, least SLHPR, or merely politics, since the LRU should last much longer based on its failure rate.

The ultimate evaluation involves comparing the cost of the true versus historical system using the DEPCOST model directly. A comparison of cost *and* MTBUR can be accomplished by viewing figures 18 and 19. These figures are constructed by modifying the MTBUR input column of the DEPCOST model to reflect first historical values and then predicted values of MTBUR. The 450°F thermostat is extracted from subsequent analysis due to the assumed organizational factors mentioned earlier as well as the LRU impotency with respect to overall cost savings compared to all other LRUs in the system. It should be noted that in all DEPCOST analyses only one spare per LRU is considered to gain savings per unit LRU.

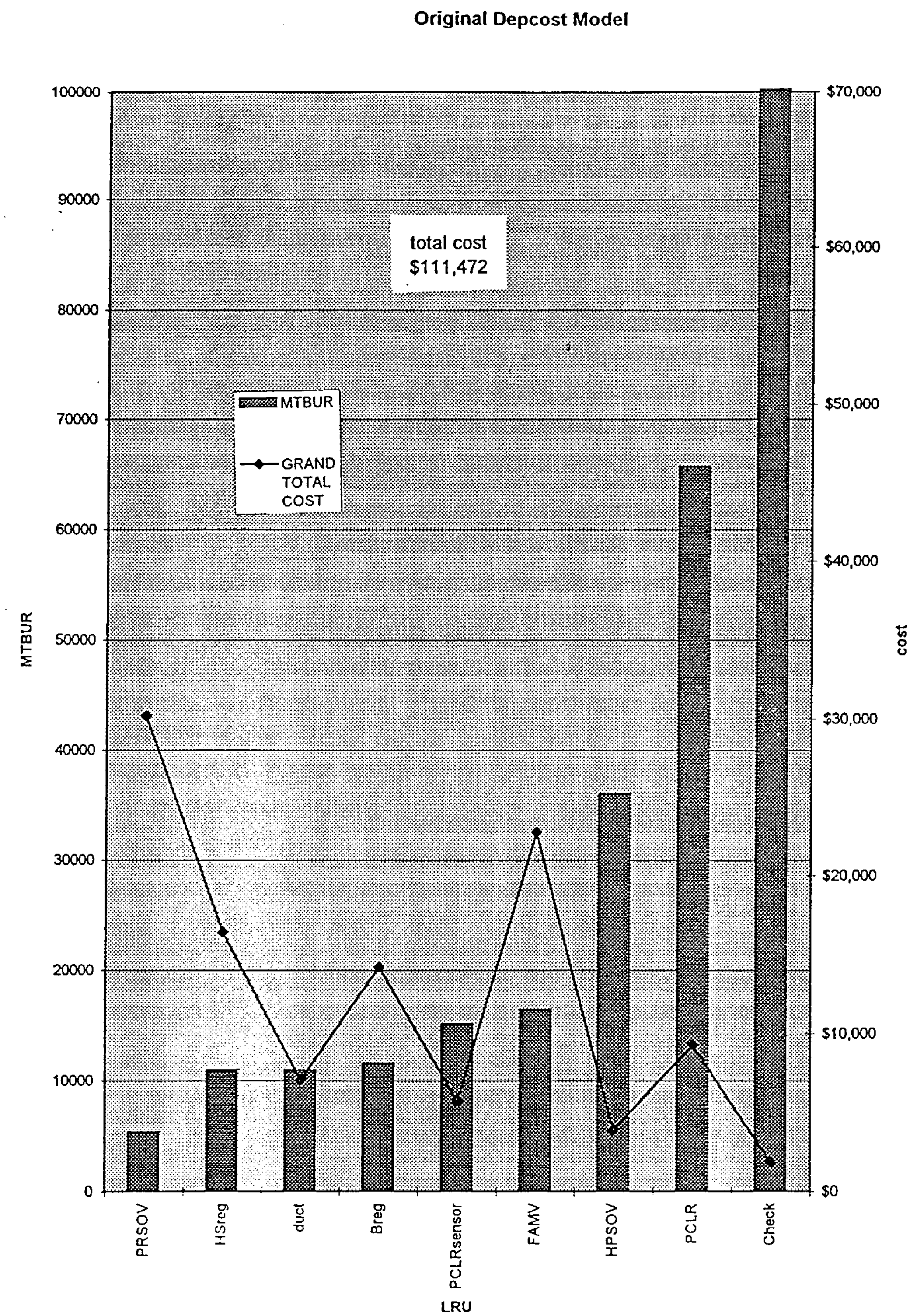


Figure 19. DEPCOST model of historical MTBURs

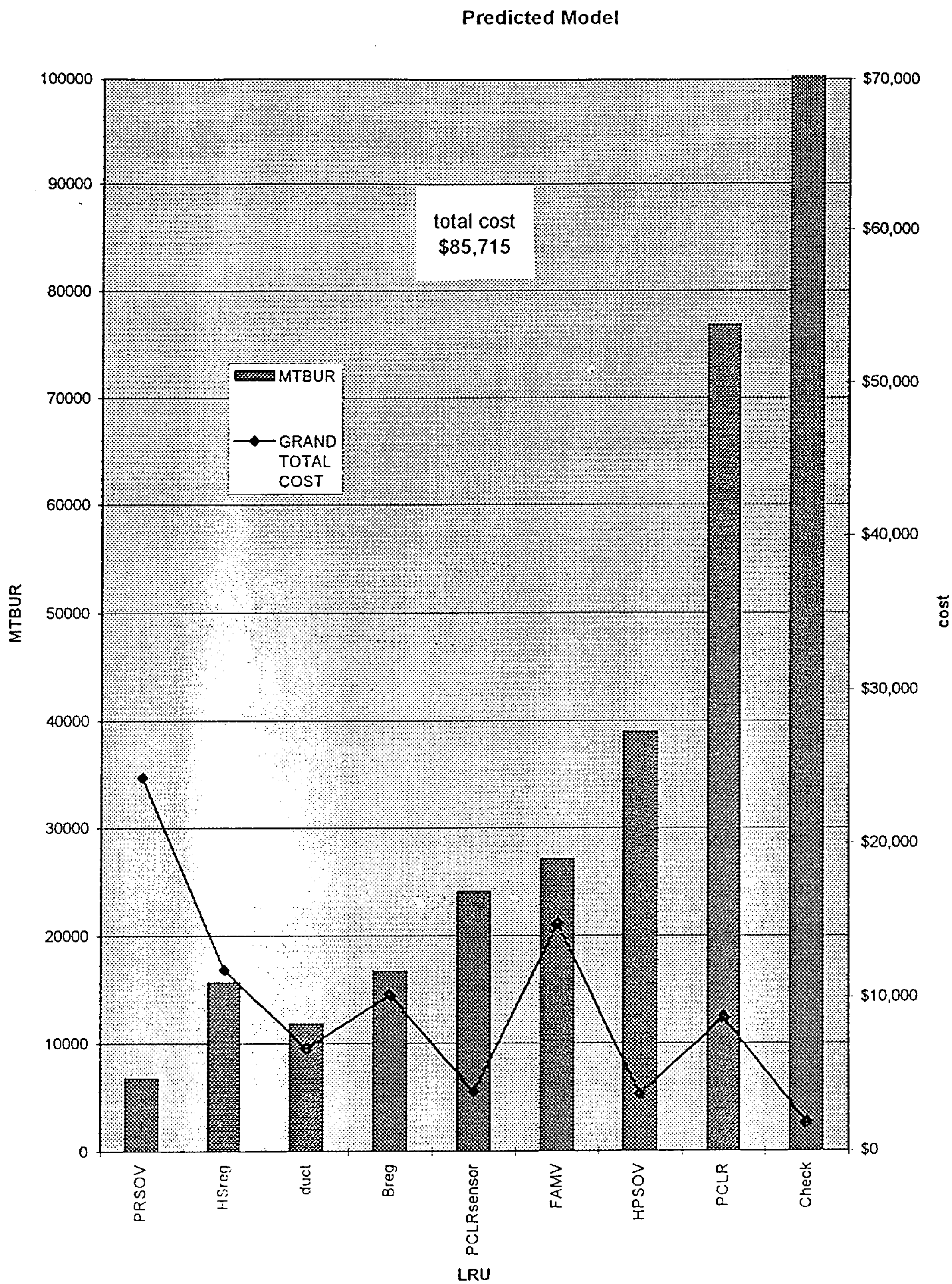


Figure 20. DEPCOST model of predicted MTBURs

Figures 18 and 19 validify the MTBUR prediction metric. Not only are predicted MTBURs and costs within an acceptable range of historical values, but order is preserved with respect to both candidates for diagnosability problems and cost drivers. With this information, the choice of LRUs and functions for redesign can be easily made.

Since no passive failures are addressed in this research one would anticipate a higher predicted MTBUR and therefore a lower cost than the historical values as figures 18 and 19 illustrate. A sample DEPCOST model spreadsheet can be found in appendix C (for analysis, all information not pertaining to this research is extracted).

5.2 System Modification and Comparison

All redesigns are based on not only diagnosability improvements, but also on cost savings since as noted in section 2.0, cost is always the common denominator. Seven design modifications are studied and evaluations for each based on feasibility and logic are given in accordance with the design/redesign methodology discussed in section 4.3. The benchmark for all design comparisons is the original design using predicted values of MTBUR for continuity. A sample spreadsheet analysis and DEPCOST illustration for each change is located in appendix C.

5.2.1 Change 1--Remove Pressure Function from PRSOV

Since the PRSOV was a point of interest in previous research involving the 747-400 BACS, and apparently is in the present analysis as well, the most successful system change suggested in that analysis (Clark, 1993) is incorporated in the first modification. This change follows all suggestions found in section 4.3 and involves essentially removing the pressure regulating function of the PRSOV.

Like the temperature control function, the pressure control function of the PRSOV is shared by other LRUs. In this case, the pressure is regulated directly at the high and low pressure ports instead of at the junction of the two just prior to the precooler. This change requires the check valve to be replaced by a control valve. Also, the Breg must then be moved to the new control valve to monitor downstream pressure and signal a bleed trip off indication in the event of an overpressurization.

Based on benchmark MTBUR and cost, change 1 increases the MTBUR for the PRSOV by 51 percent, decreases the MTBUR for the check valve by 79 percent, and slightly decreases the MTBUR for the Breg. Since the check valve is converted to a control valve, the failure rate of its counterpart control valve, the HPSOV, is assigned to the check valve bringing its MTBUR down exponentially. Since the check valve is more resistant to cost change than the PRSOV due to labor time and ambiguity, overall cost is in favor of the PRSOV. The cost savings for this system change is on the order of 8 percent--a significant amount based on the size and complexity of an aircraft system.

The feasibility of this design change can be approached from two directions. The number of LRUs remains constant, and hence the complexity does not increase nor do the functional requirements change drastically. Even the relationship of the Breg is not significantly altered since it was remotely located from the PRSOV anyway. Yet, considering the limited amount of space available in this particular system, any change in size and complexity at the LRU level could be restrictive, i.e., making the check valve a control valve. Also, keeping the bleed trip off functional relationship with the PRSOV requires an additional control line from the Breg.

For an original design for future aircraft (737-600,700,800...) change 1 is a feasible and logical design to address the unjustifiable removal problem, but a "quick fix" for current aircraft it is not.

5.2.2 Change 2--Add PRSOV Closed Sensor Light

Once again, the methodology suggestions of section 4.3 are heeded and the PRSOV is targeted once more. Using an existing design modification based on the 747-400 BACS design, a PRSOV closed sensor light/indication is added to the system to arrest the unjustifiable removals of at least that particular LRU. Since 70 percent of the PRSOV failure modes are in the closed position, this modification promises significant impact.

Basically, this modification entails simply adding a limit switch type sensor to give the aircraft crew, and thus troubleshooting personnel, an indication when the valve is in its closed position (indication 6 for analysis). Thus, if an indication 2 (bleed pressure low) occurs without an indication 6 (PRSOV closed) then a PRSOV failure can be discounted. This decrease in ambiguity of indication 2, which is the most ambiguous, should aid in overall system diagnosability.

Based on the benchmark, MTBUR of the PRSOV increases by 34 percent and all other MTBURs increase slightly as well with the exception of the check valve's decreasing slightly because of the system metric dynamics (the ambiguity of the check valve's only indication, 2, mandates an increase in false detections of low failure rate LRUs with a decrease in number high failure rate candidates). Overall cost savings is approximately 7 1/2 percent.

This modification exemplifies the age old battle between BITE and increased weight and complexity. Modern sensors have a reliability of at least an order of magnitude above that of the parent system and weigh as little as a dime, yet even the slightest increase in weight and complexity can substantially increase cost in terms of fuel and assembly hours--especially for aircraft systems. From the human factors standpoint, there is a point of diminishing returns on information available to crewmembers in the form of indications, but since this indication is continuous and can be recorded, reaching that point from this indication is doubtful.

Since so many system variables comprise fuel saving strategies, the cost benefit seems to be in favor of increased weight based on the amount of savings this change

produces. Even in this particular system, there is always enough room under the cowling for "just one more sensor".

5.2.3 Change 3--Add Indication 3 to PRSOV

Targeting the PRSOV once again since it appears to have the most room for improvement, the function-indication relationship is modified to decrease the ambiguity of indication 2 in much the same way as adding a sensor.

Some type of relationship with existing indications or LRUs and the PRSOV is sought after because of the high failure rate of the PRSOV in the closed position. Considering the bleed trip off light illuminates whenever a bleed trip occurs and a bleed trip closes the PRSOV in the case of overheat or overpressure, an association is already in place. Merely running the bleed trip off light (indicator 3) wire from the PRSOV closed position instead of the overheat/overtemperature probes which currently signal the indication not only reduces the ambiguity of indication 2, but maintains system integrity by changing no functions and adding no sensors. This modification simply changes the PRSOV failed closed indication from indication 2 to indication 23.

The MTBUR for the PRSOV increases by 29 percent and slightly increases for the HSreg, duct, Breg, HPSOV, and PCLR primarily due to the decrease in ambiguity of indication 2 which these LRUs share. All other LRU MTBURs decrease slightly due to associations with both indications 2 and 3 (except for the check valve whose MTBUR decreases for the same reason stated in section 5.2.2) which the PRSOV is now associated with. The overall cost savings for this modification is almost 6 1/2 percent.

This modification seems very feasible due mainly to its simplicity. According to Boeing publications the bleed trip off light is incited by an overpressure ($>180 \pm 10$ psi) at the inlet of the PRSOV which is monitored by an overpressure switch inside the remotely located Breg. The indication is also incited by an overheat ($>490°\pm10°$F) out

of the precooler which is monitored by an overheat switch just downstream of the precooler. This change would replace two wires running from the switches with one wire running only from the PRSOV to the bleed switch off light. A drawback would be an apparent need to install a limit switch sensor in the PRSOV to monitor its position and relay the message to the indication, therefore adding a sensor like change 2 but not decreasing the ambiguity as much as a separate indication might.

Overall, this design mentality is logical. Scrutiny reveals that complexity is even reduced if the bleed trip off light signal wires are removed from the Breg overpressure and overtemperature switches. Of course, a modification like this may take more hours of overhaul than desired. In addition, even though indication 2 decreases in ambiguity, indication 23 increases in ambiguity. In light of the above discussion, change 3 promises to be a sound design.

5.2.4 Change 4--Add Indication 3 to PRSOV and FAMV

From the original DEPCOST analysis it appears that besides the PRSOV, the FAMV is next in line for room for possible improvement based on the suggestions of section 4.3. Since the FAMV already has a sometimes relationship with indication 3, making it a hard failure (always relationship) does not seem out of the question.

From a mechanical standpoint, whenever the FAMV fails in the closed position, the PCLR will not receive any cooling air from the engine fan. This should cause an overheat condition an overwhelming majority of the time. A wire and probably a limit switch sensor must be added to the FAMV to incite the bleed trip off light whenever a failure occurs. This modification is applied in conjunction with the modification in the previous section for analysis purposes.

From the original benchmark, the MTBUR of the PRSOV increases by 22 percent. All other LRUs are affected in the approximately the same manner and same degree as the previous change. Even, the MTBUR of the FAMV is decreased slightly. The overall cost savings is almost 6 percent--less than that of change 3 alone.

The faulty logic in this redesign is that it increases the failure rate of an already high failure rate indication (23) at least as much as it decreases the failure rate of an already improved indication (2). Thus nullifying any gains previously made. Also, even though the FAMV has much room for improvement, it does not have much room in the particular failure mode targeted (only 30 percent of all failures are in the closed mode). From a mechanical standpoint, the same arguments apply as those given against modification 3, but twofold since another sensor must be added.

Not only must an LRU with a high potential for improvement be targeted, but the particular failure mode that causes most of its failures must be addressed. Modification 4 is not recommended.

5.2.5 Change 5--Add PRSOV Closed & FAMV Open Sensors

The lesson learned from the previous section is applied by combining change 2 from the 747 design to a sensor addition on the FAMV. The open position of the FAMV valve along with the closed position of the PRSOV is targeted by adding two sensors to the system.

In addition to the PRSOV modification discussed in section 5.2.2, a limit switch sensor must be added to monitor the failed open position of the FAMV which accounts for 70 percent of its failures. These two sensors decrease the ambiguity of two ambiguous indications (2 and 5) while increasing the diagnosability of the two highest cost drivers.

The MTBURs of the PRSOV, PCLRsen, and FAMV are significantly increased while those of the HSreg, duct, Breg, and HPSOV are increased slightly. The PCLR and check MTBURs are decreased slightly due to their increase in probability of false detection which influences cost little. The overall cost savings is over 10 percent.

The BITE versus weight and complexity conflict arises again for this configuration. The cost analysis of added weight is not included in this research, but it is doubtful cost would encroach upon the savings realized by two lightweight sensors.

5.2.6 Change 6--Add PRSOV Closed & FAMV Stuck Sensors

Iterating the previous change one more step to arrest all unjustifiable removals of the FAMV, a "stuck" sensor added in lieu of a stuck open sensor. The FAMV is the second highest cost LRU in terms of replacements and definitely a cost driver in terms of diagnosability so this modification is analyzed with optimism.

Preferably, a stuck sensor would be no more complex than a single limit switch. Since the LRU in question consists of a butterfly valve, a sensor placed on the axis of the valve could monitor any movement, or lack thereof. No additional sense lines would be necessary from the previous modification. Worst case, two limit switches (open and closed) would be required.

The analysis shows significant increases in all LRU MTBURs especially the PRSOV (34 percent) and FAMV (25 percent). The overall cost savings is 12 percent.

By virtually eliminating all unjustifiable removals of the FAMV (reducing MTBUR to MTBF of the LRU), a relatively simple modification realizes almost twice the savings as the 747 design.

5.2.7 Change 7--Add PRSOV & FAMV Stuck Sensors

The final modification of this analysis iterates the previous modification one more time by incorporating a "stuck" sensor of both the PRSOV and FAMV. This modification essentially eliminates all unjustifiable removals of the two least diagnosable/highest cost drivers in the pneumatic system.

Both the PRSOV and FAMV incorporate butterfly-type valves for their operation so both could be fitted with the same "stuck" sensor mentioned in section 5.2.6. Once again, complexity is not increased to a great extent and added weight does not seem to threaten feasibility.

Based on the benchmark once more, all LRU MTBURs realize a rather tremendous increase: PRSOV 65 percent; PCLRsen 54 percent; FAMV 25 percent; and all others over 3 percent. The overall cost savings is over 16 percent.

This change is recommended over all other changes due to its simplicity and ease of retrofitting current aircraft designs. Information from the Boeing company and the Federal Aviation Administration (FAA) implies bigger cost savings realized on sensor-based modifications rather than complete component overhaul do to certification practices. Change 7 of the BACS MTBUR based research analysis possesses the confident expectation of most cost-benefit and least retrofit time loss. A summary of modification results based on predicted diagnosability cost is shown in table 3.

Original design cost = $85,715		
DESIGN	**COST**	**% SAVINGS**
Change 1	$78,673	8.2
Change 2	$79,316	7.5
Change 3	$80,187	6.5
Change 4	$80,696	5.9
Change 5	$77,032	10.1
Change 6	$75,293	12.2
Change 7	$71,715	16.3

Table 3. Cost analysis of modifications.

5.3 Spares Provisioning

All prior cost analyses consider only the cost per unit LRU. The DEPCOST model includes a spares holding cost found by equation 21.

$$SparesHoldingCost = NumberofSpares \times CostPerSpareUnit\left[\left(\frac{i(1+i)^{SystemLife}}{(1+i)^{SystemLife}-1}\right)+SparesHoldingFactor\right] \qquad (21)$$

where i=(MARR-Inflation Rate)/(1+Inflation Rate).

If the number of spares is found using a Poisson distribution with a spares availability of 95 percent, a change in LRU MTBUR is likely to have an impact on overall diagnosability cost.

The Boeing Company's algorithm for computing the number of spares is based on the Poisson expansion of

$$\sum_{i=1}^{r}\left[\left(e^{-N}\right)*(N^{i})\right]/\,i! > fillrate(0.95) \qquad (22)$$

where e is the natural logarithmic base, r+1 is the number of required spares to satisfy the fill rate, and N is found from equation 23.

$$N = QPA * FlightHours * TurnDays * RR / 365 \qquad (23)$$

where QPA is the quantity per airplane, FlightHours is the fleet size multiplied by the average flight hours per airplane in one year, the TurnDays is the time in the shop (14 days for electrical components and 30 days for mechanical components), and RR is the removal rate which is the inverse of MTBUR. An increase in MTBUR should decrease the cost of the system since it is inversely proportional to the number of spares, and therefore the holding cost.

Incorporating the required number of spares for the system, an overall system cost comparison can be made. Table 4 presents a summary of the modification results to include the cost of actual spares provisioning.

Original design cost = $122,258		
DESIGN	**COST**	**% SAVINGS**
Change 1	$112,443	8.0
Change 2	$113,085	7.5
Change 3	$115,343	5.7
Change 4	$115,852	5.2
Change 5	$107,651	12.0
Change 6	$105,912	13.4
Change 7	$102,334	16.3

Table 4. Cost analysis of modifications including spares provisioning.

Actual spares provisioning reveals less savings for changes 3 and 4, but an increase in savings for changes 5 and 6. The majority of cost savings from the decrease in the number of required spares is due to the PRSOV and FAMV, falling directly in line with the redesign methodology of section 4.3.

6.0 CONCLUSION

The growing life cycle cost dependency of quality products is prompting design engineers to meet product specifications with diagnosability as a major ingredient. This research has addressed diagnosability analysis for mechanical systems quantitatively by means of LRU-indication relationships. These relationships, along with structure which is defined by maintenance time, essentially determine the diagnosability of a system. As system LRU functions and indications are modified, diagnosability also changes based on the reliability of each LRU and the ambiguity of each indication.

The MTBUR of each system LRU is a direct measure of diagnosability. A generic metric was developed to predict LRU MTBURs for any system made up of several LRUs that give some indication of failure. The MTBUR of a particular LRU is directly related to the probability of detecting that particular LRU and its time to repair given a failure indication including other LRUs. The value of MTBUR for each LRU can be compared to that of other LRUs to determine which ones present a diagnostic challenge. System changes based on this information can then be made to decrease the cost of diagnosability.

The MTBUR prediction metric was applied to the 737 BACS to determine system improvements. LRU evaluation presented the PRSOV and FAMV as primary candidates for diagnosability improvement. The life cycle costing mechanism, DEPCOST model, was used to evaluate system cost based on the diagnosability parameters of unjustified removals, spares cost, and maintenance time. Seven design changes were suggested and analyzed based on MTBUR, cost, and feasibility. These redesigns modify LRU indications by optimizing current indications or by adding sensors to strategic LRUs. Evaluations of the redesigns revealed an improvement in diagnosability directly impacting the cost of the system.

Quality through diagnosability cannot be neglected in today's marketplace. With cost as the common metric for design evaluation, and analysis factors contributing to extensive downtime costs, design for diagnosability should be more than mere

happenstance considered after the product is launched. The relationships of diagnosability developed here can be directly compared with other common design decision-making variables such as manufacturability and ease of assembly in the arena of life cycle costing. The direction of future research is expected to address the structure of designs explicitly in terms of maintenance hours. This will especially enhance prediction techniques of systems with a lack of historical data.

REFERENCES

1. Ali, Adel A., "Performance Models of Testability", *Final Technical Report for Contract No. N00019-83-C-0327*, Naval Air Systems Command, Department of the Navy, Washington D.C., 1984.

2. Annis, Charles, "Estimating The Probability of Early Failure in Engineering Structures", *Proceedings of the annual meeting of the American Society of Mechanical Engineers*, 1992, pp33-41

3. Ascher, H. and Feingold, H., *Repairable Systems Reliability*, Marcel Dekker, New York, 1984

4. Babb, A. H. and Smith, D. J., *Maintainability Engineering*, John Wiley and Sons, New York, 1973

5. Berggren, C. J., "Malfunction Diagnosis of Rolling Element Bearings", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp157-172

6. Black, Philip, "Troubleshooting with LANs & Smart Sensors", *INTECH*, May 1994, 41, pp29-31

7. Blanchard, B.S., Verma, D., and Peterson, E.L., *Maintainability*, John Wiley & Sons, New York, 1995

8. Caroli, J.A. and Lyne, G.W., "A Testability-Dependent Maintainability-Prediction Technique", *Proceedings of the annual Reliability and Maintainability Symposium*, 1992, pp223-227

9. Carr, Wendell E., *Statistical Problem Solving*, Marcel Dekker, New York, 1992

10. Carrubba, E.R. and Gordon, R.D., *Product Assurance Principles*, McGraw-Hill Inc., 1988

11. Clark, Garrett, "Diagnostic Modeling and Diagnosability Evaluation for Mechanical Systems", M.S. Thesis, Department of Mechanical Engineering, Oregon State University, Corvallis, Oregon, 1993

12. DiMarko, P., Eubanks, C.F., and Ishii, K., "Service Modes and Effects Analysis: Integration of Failure Analysis and Serviceability Design", Submitted to the ASME Computers In Engineering Conference, 1995

13. Goble, William M., "Just How Expensive Is Your Control System?", *INTECH*, May 1994, 41, pp33-36

14. Gilmore, H.L. and Schwartz, H.C., *Integrated Product Testing and Evaluation*, Marcel Dekker, New York, 1986

15. Harker, R.G., "The Impact of Microprocessors on Rotary Machinery Data Acquisition and Diagnostic Information Systems", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp87-98

16. Jagger, D.H., "Advances in Design and Testing for Failure Prevention in Aircraft", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp173-187

17. Jordan, M.F. and Keshishian, V.M., "Mathematical Model for Predicting Manhours Savings from On-Board Diagnostics and BIT/BITE", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp81-86

18. Kapur, K.C. and Lamberson, L. R., *Reliability in Engineering Design*, John Wiley & Sons, New York, 1977

19. Maekawa, D. and Toyota, T., "Automatic Diagnosis for Malfunction of Rotating Machines by Fault-Matrix", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp147-156

20. Marks, M.D., Eubanks, C.F., and Ishii, K., "Life-Cycle Clumping of Product Designs for Ownership and Retirement", *Design Theory and Methodology*, 53, 1993

21. Moss, Marvin A., *Designing for Minimal Maintenance Expense*, Marcel Dekker, New York, 1985

22. Palko, Ed, "Applying Portable Vibration Monitoring Instruments," *Plant Engineering*, 48, pp62-5, 1994

23. Priest, John W., *Engineering Design for Producibility and Reliability*, Marcel Dekker, New York, 1988

24. Raheja, Dev G., *Assurance Technologies*, McGraw-Hill, New York, 1991

25. Randall, R.B.,"The Application of Cepstrum Analysis to Machine Diagnostics", *Proceedings of the 36th Meeting of the Mechanical Failures Prevention Group*, 1982, pp64-72

26. Shah, P.C. and Udwadia, F.E.,"A Methodology for Optimal Sensor Locations for Identification of Dynamic Systems", *Journal of Applied Mechanics*, March 1978, 45, pp188-196

27. Souder, W.,"Management Decision Method for Managers of Engineering and Research", Van Nostrand Reinhold, New York, 1980

28. Stander, C.,"Fault Isolation BITE fro Increased Productivity", Proceedings of the annual Reliability and Maintainability Symposium, 1982, pp365-369

29. Thompson, D.E. and Fecke, T.G., "Air Force Perspective on Probabilistic Design", *Proceedings of the annual meeting of the American Society of Mechanical Engineers*, 1992, pp25-31

30. Winter, B.B., "Optimal Diagnostic Procedures", IRE Transactions on Reliability and Quality Control, 1960, pp13-19

31. Wong, Bryan, "Diagnosability Analysis for Mechanical Systems and Human Factors in Diagnosability", M.S. Thesis, Department of Mechanical Engineering, Oregon State University, Corvallis, Oregon, 1994

APPENDICES

APPENDIX A

Diagnosability Analysis Tools

SHEET 1 OF 1

ENTRY	NAME	PART NUMBER	FUNCTIONS PERFORMED BY ITEM UNDER ANALYSIS
ITEM UNDER ANALYSIS	Radiator assy.	703411	Transfer heat from coolant to ambient air
NEXT HIGHER ASSEMBLY	Engine heat transfer S/S	700400	
SUBSYSTEM	(Same as NHA)		

	FAILURE EVENT - 1.1 MODE	1.2 SOURCE CODE	1.2 SOURCE NAME	1.2 SOURCE NUMBER	1.3 RATE (FPMH)	1.4 LIFE LIMIT	1.5 EFFECT
1	Loss of coolant (leakage)	1.1	Radiator core	703423	[illegible]000		E-2
		1.2	Pressure cap	811-47R	500	5 yrs.	E-2
2	Restriction - blockage of flow	2.1	Radiator core	703423	240		E-2
3	Coolant temp. stays below spec. steady-state range	3.1	Thermostat	722173	3000		G-1

MODE	SERVICING - 2.1 TASK	2.2 PURPOSE	2.3 FREQUENCY
1	Check coolant level in overflow reservoir and radiator		once weekly; once monthly
2	Flush radiator per MP-1077	remove solid particles & gelled water	once yearly
3	None		

MODE	MONITORING - 3.1 CONDITION	3.2 CRITERION	3.3 FREQUENCY
1	Coolant temperature (gage on dash)	> 180°F	5-minute intervals
2	(same as for Mode 1)	(same as for Mode 1)	(same as for Mode 1)
3	(same as for Mode 1)	< 155°F	5 minutes after each cold start

MODE	ASSESSMENT - 4.1 CONDITION	4.2 CRITERION	4.3 FREQUENCY
1	Puddling beneath vehicle	Presence of puddle	daily
2	Rate of draining during flushing	abnormally slow	once yearly (while flushing)
3	None		

Figure A1. Reliability Centered Maintenance Form

Frequency-Based Vibration Troubleshooting Checklist

Vibration Frequency	Possible Cause	Comments
1 × Rpm	Imbalance	Steady phase that follows the transducer. Can be caused by load variation, material buildup, or pump cavitation.
	Misalignment or bent shaft	High axial levels. 180-deg phase relation at the shaft ends. Usually accompanied by high 2 × rpm frequency.
	Strain	Caused by casing or foundation distortion, or from attached structures (e.g., piping).
	Looseness	Directional; changes with transducer location. Usually accompanied by high harmonic content and random phase.
	Resonance	Caused by attached structures; drops off sharply with change of speed.
	Electrical	Broken rotor bar in induction motor. Often accompanied by sidebands of 2 × motor slip frequency.
2 × rpm	Misalignment or bent shaft	High levels of axial vibration.
Harmonics	Looseness	Large number of harmonics; impulsive or truncated time waveform
	Rubbing	Shaft contacting machine housing.
Sub-rpm	Oil whirl	Unstable phase; typically 0.43 to 0.48 of rpm.
	Bearings	Fundamental Train = $\frac{1}{2} \times \frac{RPM}{60} [1 - \frac{\text{Ball Diameter}}{\text{Pitch Diameter}} \times \text{COS contact angle}]$
N × rpm	Rolling element bearings	Inner race = $\frac{\#\text{Balls}}{2} \times \frac{RPM}{60} [1 + \frac{\text{Ball Diameter}}{\text{Pitch Diameter}} \times \text{COS contact angle}]$ Outer race = $\frac{\#\text{Balls}}{2} \times \frac{RPM}{60} [1 - \frac{\text{Ball Diameter}}{\text{Pitch Diameter}} \times \text{COS contact angle}]$ Ball defect = $\frac{\text{Pitch Diameter}}{2 \times \text{Ball Diameter}} \times \frac{RPM}{60} [1 - (\frac{\text{Ball Diameter}}{\text{Pitch Diameter}} \times (\text{COS contact angle})^2)]$ Usually modulated by running speed.
	Gears	Gearmesh (#teeth × RPM); usually modulated by running speed.
	Belts	Belt × running speed and 2 × running speed.
	Blades/vanes	#Blades/vanes × rpm; usually present in a normally-running machine. Harmonics indicate that a problem exists.
	Resonance	A number of possible sources, including shaft, casing, foundation, and attached structures. Frequency is proportional to stiffness and inversely proportional to mass. Run-up tests and modal analysis are useful in diagnosis.

(Adapted from material furnished by DLI Engineering Corp.)

Figure A2. FFT troubleshooting checklist

APPENDIX B

MTBUR Calculations

LRU	fail rate	MTBF	PC	LLHPR	SLHPR
hpsov	13.882	72035.73	0.0013882	4.5	4.64
prsov	89.135	11218.94	0.0089135	3.05	4.64
pclr	8.804	113584.7	0.0008804	4	10
duct	45.455	21999.78	0.0045455	4	2
famv	29.578	33808.91	0.0029578	7.66	8.92
check	1.34	746268.7	0.000134	4	1.8
HSreg	37.67	26546.32	0.003767	3.13	5.38
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53
Breg	43.077	23214.24	0.0043077	9.94	5.38
Thermo	9.058	110399.6	0.0009058	4.15	1.39

737-300,400,500

prsov
i= 89.135

		sum FRs per ind	# of candidates	PCi/HPRi normali	1/failrateind*1e6	sum FRn-FRi|ind	1/FRn-i	MTBFn-i/PDi	1/MTBURiun*1e6
Indication	candidates	failrateind	Ci	PDi	MTBFind	failraten-i	MTBFn-i	MTBURi-u	failratei-u
1	h,pr,H,B	70.85485	4	0.470195	14113.36	44.11435	22668.36	48210.564	20.74234
13	h,H	4.4611	2		224160		0	0	0
2	h,pr,pc,d,f,c,H,P,B,T	151.756	10	0.418728	6589.525	89.3615	11190.5	26725.009	37.41813
23	d,f,P	4.5919	3		217774.8		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445622.9		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
3	d,T	9.0613	2		110359.4		0	0	0
4	pc,d	2.71295	2		368602.4		0	0	0
5	d,f,P	33.83175	3		29558.03		0	0	0

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	13	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	2	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	23	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	3	2	0.9091
	4	5	2.27275
	5	3	1.36365

LRU	indication	% of FR	failrateperind
famv	2	25	7.3945
	23	5	1.4789
	5	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	13	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	23	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	3	90	8.1522

Totals

sum FRn-i column	1/Tot FRn-i *1e6	sum FRiu column	1/FRiu *1e6	MTBFi
Tot Failrate n-i	Tot MTBF n-i	failratei-u	MTBUR i-u	MTBUR i-j
133.47585	7491.9919970541	58.16048	17193.807	11218.94

	1/(1/MTBURun+1/MTBURj)		
Predicted	MTBUR i		Historical MTBUR i
	6789.0747		5394

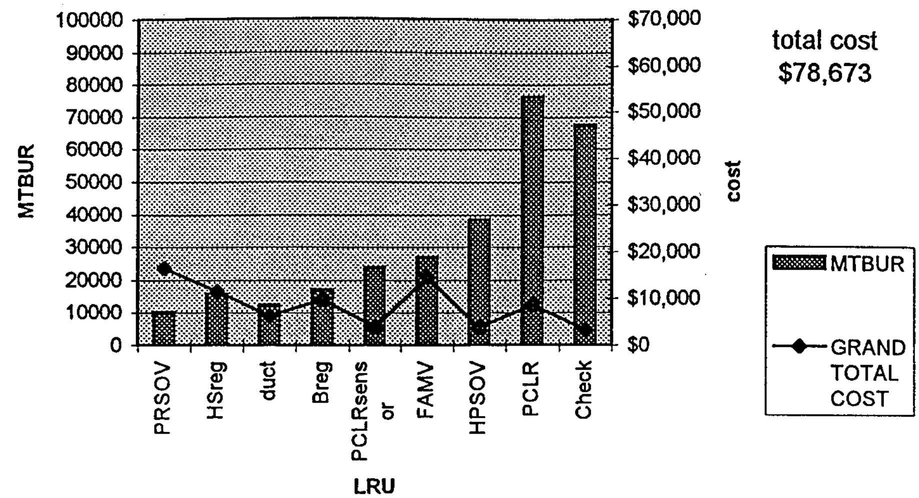
Figure B1. Sample Quattro Pro MTBUR calculation spreadsheet

APPENDIX C

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Comp Inputs / Calculate	Right >>										<< Left	Right >>							<< Left	Right >>
2	Output Totals / Up ^^	Down vv																			
3	DEPENDABILITY COST MODEL			ATA System	ATA Chapter <<< Automatic Calculation	3rd Digit >>> Automatic Calculation	Component Number	Nomenclature		Collapse INPUT Section >> Series	Quantity Per Airplane	Cost Per Spare Unit	MTBUR	MTBF	Maint. Actions Per 1000 Flight Hours	Line Labor Hours Per Removal	Line Labor Hours Per Maint. Action	Shop Labor Hours Per Removal	Shop Material Cost Per Failure	Sched. Maint. Labor Hours Per 1000 Flight Hours	Sched. Maint. Material Cost Per 1000 Flight Hours
4	Last edit 8/23/95 - DeJong has notes below			36-11-144-051	36	1		CNTLR, -300 PRSOV/RVS FLOW(REQLR)		PRSOV	2	$6,206	8789	11219		3.05		4.64			
5	AIRPLANE INFORMATION			36-11-142-031	36	1		CONT, HIGH STAGE BLEED AIR SOV		HSreg	2	$3,463	15659	28547		3.13		5.38			
6	Model	737		36-15-192-121	36	1		DUCT, FSLG CAIR DISTN (GENRL)		duct	1	$7,000	11827	110000		4.00		2.00			
7	Flights Per Year Per Airplane	2120		36-11-000-001	36	1		BLEED AIR CONT AND DISTN - GENRL		lhreg	1	$4,000	18700	23214		9.84		5.38			
8	Flight Hours Per Flight	1.38		36-12-400-151	36	1		SENSR, PCOOL FAN AIR MODULO CTVLV		PCLRsensor	2	$3,278	24108	58505		2.24		1.53			
9	Delay Cost Per Delay Hour	2,700		36-12-676-441	36	1		VALVE, PCOOL FAN AIR MODULO CONT		FAMV	2	$10,621	27123	33809		7.66		8.82			
10	Cancellation Cost	8,200		36-11-576-321	36	1		VALVE, ENG HIGH STAGE BLEED(GENRL)		HPSOV	1	$6,000	38931	72036		4.50		4.64			
11	Air Turn Back Cost	8,300		36-12-206-011	36	1		EXCHR, ENG BOAIR HEAT (PCOOL)		PCLR	2	$22,352	76841	113583		4.00		10.00			
12	Diversion Cost	8,200		36-11-576-032	36	1		VALVE, 5TH STAGE BLEED AIR CHECK		Check	2	$8,582	319140	746312		4.00		1.80			
13	Fleet Size	50																			
14																					
15	ECONOMIC FACTORS																				
16	Maintenance Labor Burden Factor	2.1		36-11-536-011	36	1		THRMT, ENG BOAIR 450 DEG		Thermo	2	$3,191	89645	110400		4.15		1.38			
17	Direct Labor Rate Per Hour	$22.75																			
18	Spares Holding Factor	12.0%																			
19	For Spreading Spares Acquisition Costs Only:																				
20	Inflation Rate	3.5%																			

	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS
1						<< Left	Right >>	<< Left																
2								Right >>																
3	Non-Routine Labor Hours Per 1000 Flight Hours	Delays Per 100 Departures	Cancellations Per 100 Departures	Air Turn Backs Per 100 Departures	Diversions Per 100 Departures	Average Delay Time (Hours)	Number of Spares	Open INPUT Section <<		Collapse OUTPUT Section >>	Line Maintenance Labor Cost	Shop Maintenance Labor Cost >> Collapse >>	Shop Maintenance Material Cost	Shop Maintenance Costs << Expand	Routine Labor and Material Cost >> Collapse >>	Non-Routine Maintenance Cost	Scheduled Maintenance Costs << Expand	Delay Cost >> Collapse >>	Cancellation Cost	Air Turn Back Cost	Diversion Cost	Schedule Interruption Costs << Expand	Spares Cost	GRAND TOTAL COST
4							1.0				$9,070	$13,804	$0	$13,804	$0	$0	$0	$0	$0	$0	$0	$0	$1,387	$24,261
5							1.0				$4,040	$8,838	$0	$8,838	$0	$0	$0	$0	$0	$0	$0	$0	$774	$11,752
6							1.0				$3,413	$1,707	$0	$1,707	$0	$0	$0	$0	$0	$0	$0	$0	$1,564	$8,884
7							1.0				$6,010	$3,251	$0	$3,251	$0	$0	$0	$0	$0	$0	$0	$0	$894	$10,155
8							1.0				$1,876	$1,277	$0	$1,277	$0	$0	$0	$0	$0	$0	$0	$0	$732	$3,885
9							1.0				$5,703	$8,835	$0	$8,835	$0	$0	$0	$0	$0	$0	$0	$0	$2,418	$14,758
10							1.0				$1,167	$1,203	$0	$1,203	$0	$0	$0	$0	$0	$0	$0	$0	$1,341	$3,710
11							1.0				$1,051	$2,827	$0	$2,827	$0	$0	$0	$0	$0	$0	$0	$0	$4,995	$8,872
12							1.0				$253	$114	$0	$114	$0	$0	$0	$0	$0	$0	$0	$0	$1,473	$1,840
13																								
14																					system minus thermo total=			$85,715
15																								
16							3.0				$934	$314	$0	$314	$0	$0	$0	$0	$0	$0	$0	$0	$2,139	$3,388
17																								
18																						system total=		$88,102
19																								
20																								

Figure C1. Sample DEPCOST model spreadsheet



LRU	fail rate	MTBF	PC	LLHPR	SLHPR
hpsov	13.882	72035.73	0.0013882	4.5	4.64
prsov	89.135	11218.94	0.0089135	3.05	4.64
pclr	8.804	113584.7	0.0008804	4	10
duct	45.455	21999.78	0.0045455	4	2
famv	29.578	33808.91	0.0029578	7.66	8.92
check	13.882	72035.73	0.0013882	4	1.8
HSreg	37.67	26546.32	0.003767	3.13	5.38
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53
Breg	43.077	23214.24	0.0043077	9.94	5.38
Thermo	9.058	110399.6	0.0009058	4.15	1.39

737-300,400,500

prsov
i= 89.135

Indication	candidates	failrateind (sum FRs per ind)	Ci (# of candidates)	PDi (PCi/HPRi normal)	MTBFind (1/failrateind*1e6)	failraten-i (sum FRn-FRi/ind)	MTBFn-i (1/FRn-i)	MTBURi-u (MTBFn-i/PDi)	failratei-un (1/MTBURiun*1e6)
1	h,H,B	41.9605	3		23831.94		0	0	0
13	h,H,B	6.61495	3		151172.7		0	0	0
2	h,pc,d,f,H,P,B,T	88.0215	8		11360.86		0	0	0
23	d,f,P	4.5919	3		217774.8		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445622.9		0	0	0
25	pc,d,pr,c	64.4379	4	0.964042	15518.82	2.0434	489380.4	507633.74	1.969924
3	d,T,pr	35.8018	3	0.68178	27931.56	9.0613	110359.4	161869.69	6.177809
4	pc,d	2.71295	2		368602.4		0	0	0
5	d,f,P	33.83175	3		29558.03		0	0	0

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	13	5	0.6941
	2	70	9.7174
prsov	3	30	26.7405
	25	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	23	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	3	2	0.9091
	4	5	2.27275
	5	3	1.36365

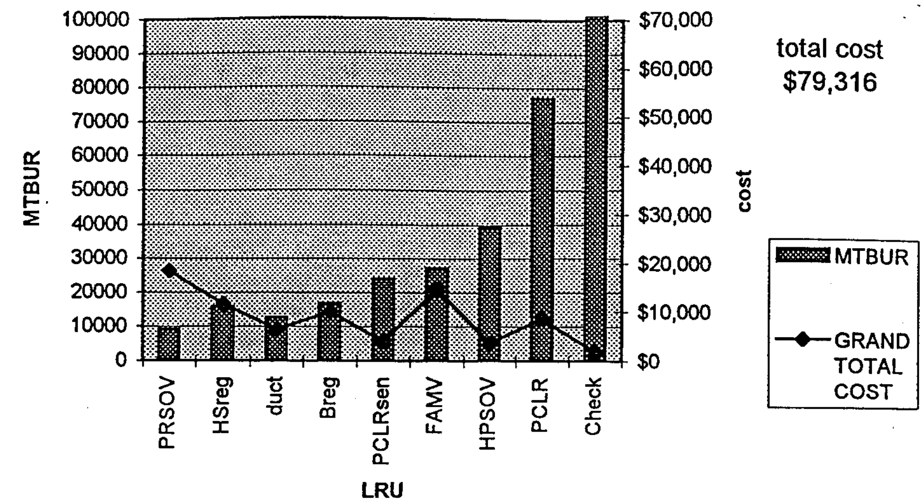
LRU	indication	% of FR	failrateperind
famv	2	25	7.3945
	23	5	1.4789
	5	70	20.7046
check	25	5	0.6941
HSreg	1	45	16.9515
	13	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	23	5	0.84025
	5	70	11.7635
Breg	1	50	21.5385
	13	5	2.15385
	2	35	15.07695
Thermo	2	10	0.9058
	3	90	8.1522

Totals

Tot Failrate n-i (sum FRn-i column)	Tot MTBF n-i (1/Tot FRn-i*1e6)	failratei-un (sum FRiu column)	MTBUR i-un (1/FRiu*1e6)	MTBUR i-j (MTBFi)
11.1047	90051.959980909	8.147733	122733.524	11218.94

Predicted MTBUR i (1/(1/MTBURun+1/MTBURj))	Historical MTBUR i
10279.3165	5394

Figure C2. Spreadsheet calculation and DEPCOST illustration for change 1



LRU	fail rate	MTBF	PC	LLHPR	SLHPR
hpsov	13.882	72035.73	0.0013882	4.5	4.64
prsov	89.135	11218.94	0.0089135	3.05	4.64
pclr	8.804	113584.7	0.0008804	4	10
duct	45.455	21999.78	0.0045455	4	2
famv	29.578	33808.91	0.0029578	7.66	8.92
check	1.34	746268.7	0.000134	4	1.8
HSreg	37.67	26546.32	0.003767	3.13	5.38
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53
Breg	43.077	23214.24	0.0043077	9.94	5.38
Thermo	9.058	110399.6	0.0009058	4.15	1.39

737-300,400,500

prsov
i= 89.135

ch 2

Indication	candidates	sum FRs per ind failrateind	# of candidates Ci	PCi/HPRi normaliz PDi	1/failrateind*1e6 MTBFind	sum FRn-FRi/ind failraten-i	1/FRn-i MTBFn-i	MTBFn-i/PDi MTBURi-u	1/MTBURiun*1e6 failratei-un
1	h,pr,H,B	70.85485	4	0.470195	14113.4	44.1144	22668.4	48210.56	20.74234
136	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,f,c,H,P,B,T	89.3615	9		11190.5		0	0	0
236	d,f,P	4.5919	3		217775		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445623		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
36	d,T	9.0613	2		110359		0	0	0
4	pc,d	2.71295	2		368602		0	0	0
5	d,f,P	33.83175	3		29558		0	0	0
26	pr	62.3945	1	1	16027.1	0	0	0	0

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	136	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	26	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	236	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	36	2	0.9091
	4	5	2.27275
	5	3	1.36365

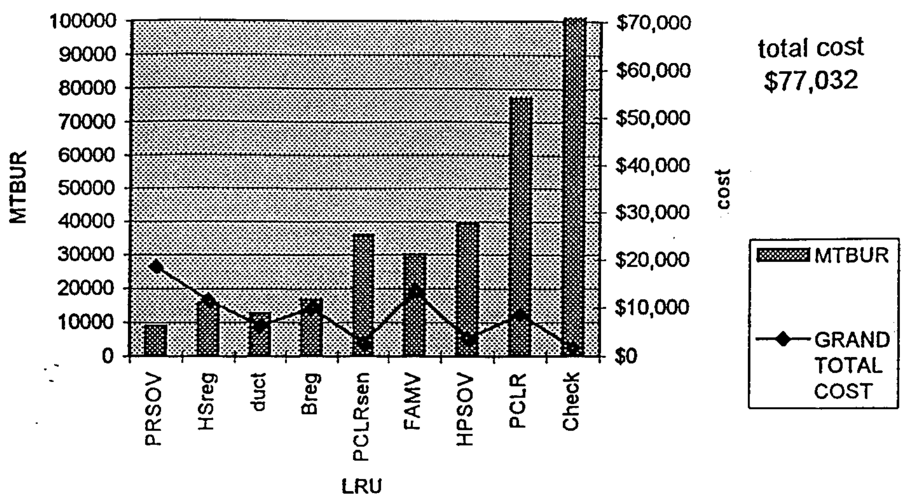
LRU	indication	% of FR	failrateperind
famv	2	25	7.3945
	236	5	1.4789
	5	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	136	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	236	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	36	90	8.1522

Totals

sum FRn-i column Tot Failrate n-i	1/Tot FRn-i *1e6 Tot MTBF n-i	sum FRiu column failratei-un	1/FRiu *1e6 MTBUR i-un	MTBFi MTBUR i-j
44.11435	22668.360748827	20.74234	48210.564	11218.94

Predicted	1/(1/MTBURun+1/MTBURj) MTBUR i	Historical MTBUR i
	9101.0574	5394

Figure C3. Spreadsheet calculation and DEPCOST illustration for change 2



LRU	fail rate	MTBF	PC	LLHPR	SLHPR		
hpsov	13.882	72035.73	0.0013882	4.5	4.64		737-300,400,500
prsov	89.135	11218.94	0.0089135	3.05	4.64		
pclr	8.804	113584.7	0.0008804	4	10		prsov
duct	45.455	21999.78	0.0045455	4	2	i=	89.135
famv	29.578	33808.91	0.0029578	7.66	8.92		
check	1.34	746268.7	0.000134	4	1.8		
HSreg	37.67	26546.32	0.003767	3.13	5.38		ch 3
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53		
Breg	43.077	23214.24	0.0043077	9.94	5.38		
Thermo	9.058	110399.6	0.0009058	4.15	1.39		

		sum FRs per ind	# of candidates	PCi/HPRi normalz	1/failrateind*1e6	sum FRn-FRi,ind	1/FRn-i	MTBFn-i/PDi	1/MTBURiun*1e6
Indication	candidates	failrateind	Ci	PDi	MTBFind	failraten-i	MTBFn-i	MTBURi-u	failratei-un
1	h,pr,H,B	70.65485	4	0.470195	14113.4	44.1144	22668.4	48210.56	20.74234
136	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,f,c,H,P,B,T	89.3615	9		11190.5		0	0	0
236	d,f,P	4.5919	3		217775		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445623		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
36	d,T	9.0613	2		110359		0	0	0
4	pc,d	2.71295	2		368602		0	0	0
5	d,P	13.12715	2		76178		0	0	0
26	pr	62.3945	1	1	16027.1	0	0	0	0
57	f	20.7046	1		48298.4				

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	136	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	26	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	236	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	36	2	0.9091
	4	5	2.27275
	5	3	1.36365

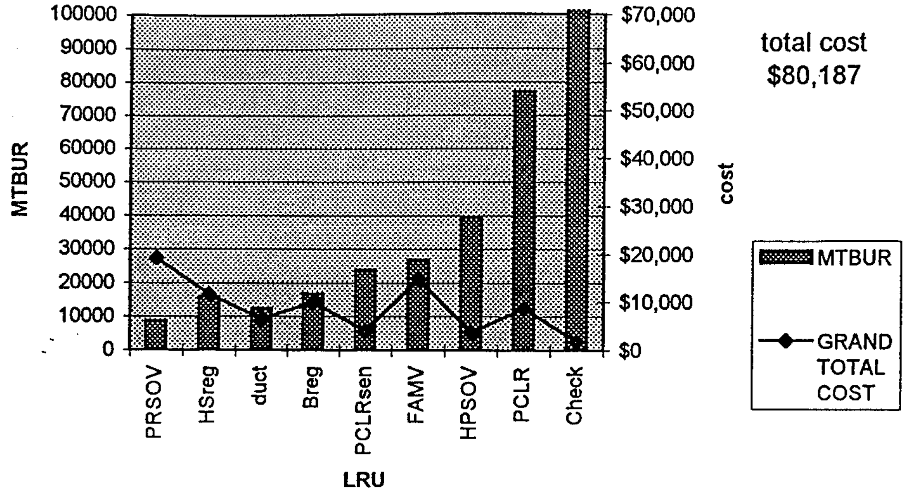
LRU	indication	% of FR	failrateperind
famv	2	25	7.3945
	236	5	1.4789
	57	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	136	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	236	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	36	90	8.1522

Totals

sum FRn-i column	1/Tot FRn-i*1e6	sum FRi-un column	1/FRi-un*1e6	MTBFi
Tot Failrate n-i	Tot MTBF n-i	failratei-un	MTBUR i-un	MTBUR i-j
44.11435	22668.360748627	20.74234	48210.564	11218.94

	1/(1/MTBURi-un+1/MTBURij)	
Predicted	MTBUR i	Historical MTBUR i
	9101.0574	5394

Figure C4. Spreadsheet calculation and DEPCOST illustration for change 3



LRU	fail rate	MTBF	PC	LLHPR	SLHPR		
hpsov	13.882	72035.73	0.0013882	4.5	4.64		737-300,400,500
prsov	89.135	11218.94	0.0089135	3.05	4.64		
pclr	8.804	113584.7	0.0008804	4	10		prsov
duct	45.455	21999.78	0.0045455	4	2	i=	89.135
famv	29.578	33808.91	0.0029578	7.66	8.92		
check	1.34	746268.7	0.000134	4	1.8		
HSreg	37.67	26546.32	0.003767	3.13	5.38		ch 4
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53		
Breg	43.077	23214.24	0.0043077	9.94	5.38		
Thermo	9.058	110399.6	0.0009058	4.15	1.39		

Indication	candidates	sum FRs per ind failrateind	# of candidates Ci	PCi/HPRi normal PDi	1/failrateind*1e6 MTBFind	sum FRn-FRijind failraten-i	1/FRn-i MTBFn-i	MTBFn-i/PDi MTBURi-u	1/MTBURiun*1e6 failratei-un
1	h,pr,H,B	70.85485	4	0.470195	14113.36	44.11435	22668.36	48210.564	20.74234
13	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,f,c,H,P,B,T	89.3615	9		11190.5		0	0	0
23	d,f,P,pr	66.9864	4	0.921533	14928.4	4.5919	217774.8	236317.88	4.231588
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445622.9		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
3	d,T	9.0613	2		110359.4		0	0	0
4	pc,d	2.71295	2		368602.4		0	0	0
5	d,f,P	33.83175	3		29558.03		0	0	0

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	13	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	23	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	23	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	3	2	0.9091
	4	5	2.27275
	5	3	1.36365

LRU	indication	% of FR	failrateperind
famv	2	25	7.3945
	23	5	1.4789
	5	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	13	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	23	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	3	90	8.1522

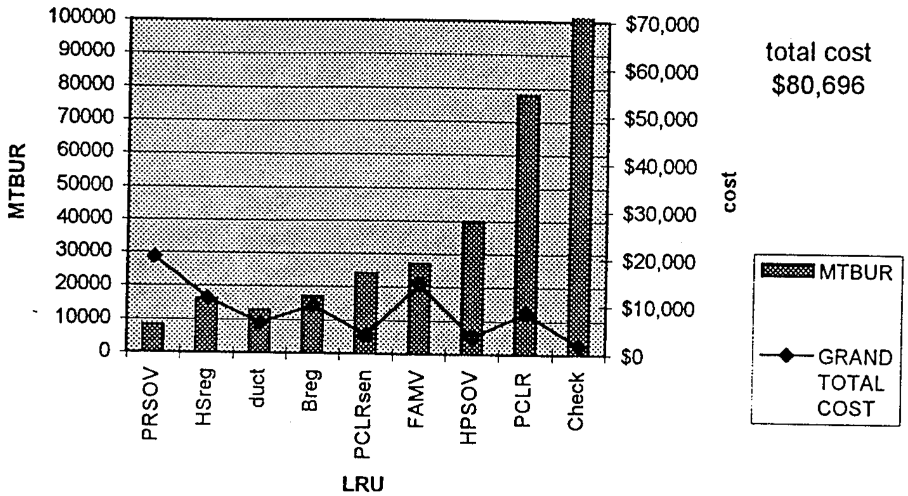
Totals

sum FRn-i column Tot Failrate n-i	1/Tot FRn-i*1e6 Tot MTBF n-i	sum FRiu column failratei-un	1/FRiu*1e6 MTBUR i-un	MTBFi MTBUR i-j
48.70625	20531.245989991	24.97393	40041.755	11218.94

Predicted	1/(1/MTBURun+1/MTBURj) MTBUR i
	8763.55599

Historical MTBUR i
5394

Figure C5. Spreadsheet calculation and DEPCOST illustration for change 4



total cost
$80,696

LRU	fail rate	MTBF	PC	LLHPR	SLHPR	
hpsov	13.882	72035.73	0.0013882	4.5	4.64	737-300,400,500
prsov	89.135	11218.94	0.0089135	3.05	4.64	
pclr	8.804	113584.7	0.0008804	4	10	prsov
duct	45.455	21999.78	0.0045455	4	2	i= 89.135
famv	29.578	33808.91	0.0029578	7.66	8.92	
check	1.34	746268.7	0.000134	4	1.8	
HSreg	37.67	26546.32	0.003767	3.13	5.38	ch 5
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53	
Breg	43.077	23214.24	0.0043077	9.94	5.38	
Thermo	9.058	110399.6	0.0009058	4.15	1.39	

		sum FRs per ind	# of candidates	PCi/HPRi normal	1/failrateind*1e6	sum FRn-FRind	1/FRn-i	MTBFn-i/PDi	1/MTBURiun*1e6
Indication	candidates	failrateind	Ci	PDi	MTBFind	failraten-i	MTBFn-i	MTBURi-u	failratei-un
1	h,pr,H,B	70.85485	4	0.470195	14113.36	44.11435	22668.36	48210.564	20.74234
13	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,c,H,P,B,T	81.967	8		12200.03		0	0	0
23	d,f,P,pr	74.3809	4	0.877104	13444.31	11.9864	83427.88	95117.413	10.51332
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445622.9		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
3	d,T	9.0613	2		110359.4		0	0	0
4	pc,d	2.71295	2		368602.4		0	0	0
5	d,f,P	33.83175	3		29558.03		0	0	0

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	13	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	23	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	23	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	3	2	0.9091
	4	5	2.27275
	5	3	1.36365

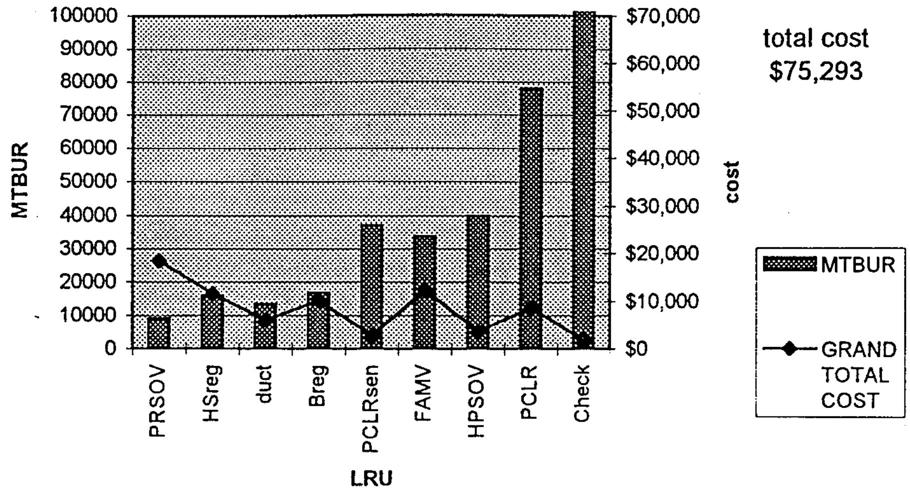
LRU	indication	% of FR	failrateperind
famv			
	23	30	8.8734
	5	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	13	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	23	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	3	90	8.1522

Totals

sum FRn-i column	1/Tot FRn-i *1e6	sum FRiu column	1/FRiu *1e6	MTBFi
Tot Failrate n-i	Tot MTBF n-i	failratei-un	MTBUR i-un	MTBUR i-j
56.10075	17825.0736398355	31.25566	31994.201	11218.94

	1/(1/MTBURun+1/MTBURj)	
Predicted	MTBUR i	Historical MTBUR i
	8306.29192	5394

Figure C6. Spreadsheet calculation and DEPCOST illustration for change 5



LRU	fail rate	MTBF	PC	LLHPR	SLHPR	
hpsov	13.882	72035.73	0.0013882	4.5	4.64	737-300,400,500
prsov	89.135	11218.94	0.0089135	3.05	4.64	
pclr	8.804	113584.7	0.0008804	4	10	prsov
duct	45.455	21999.78	0.0045455	4	2	i= 89.135
famv	29.578	33808.91	0.0029578	7.66	8.92	
check	1.34	746268.7	0.000134	4	1.8	
HSreg	37.67	26546.32	0.003767	3.13	5.38	ch 6
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53	
Breg	43.077	23214.24	0.0043077	9.94	5.38	
Thermo	9.058	110399.6	0.0009058	4.15	1.39	

Indication	candidates	sum FRs per ind failrateind	# of candidates Ci	PCi/HPRi normaliz PDi	1/failrateind*1e6 MTBFind	[illegible] failraten-i	[illegible] MTBFn-i	MTBFn-i/PDi MTBURi-u	1/MTBURiun*1e6 failratei-un
1	h,pr,H,B	70.85485	4	0.470195	14113.4	44.1144	22668.4	48210.56	20.74234
136	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,c,H,P,B,T	81.967	8		12200		0	0	0
236	d,P	3.113	2		321234		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445623		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
36	d,T	9.0613	2		110359		0	0	0
4	pc,d	2.71295	2		368602		0	0	0
5	d,P	13.12715	2		76178		0	0	0
26	pr	62.3945	1	1	16027.1	0	0	0	0
57	f	20.7046	1		48298.4				

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	136	5	0.6941
	2	70	9.7174
prsov	1	30	26.7405
	26	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	236	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	36	2	0.9091
	4	5	2.27275
	5	3	1.36365

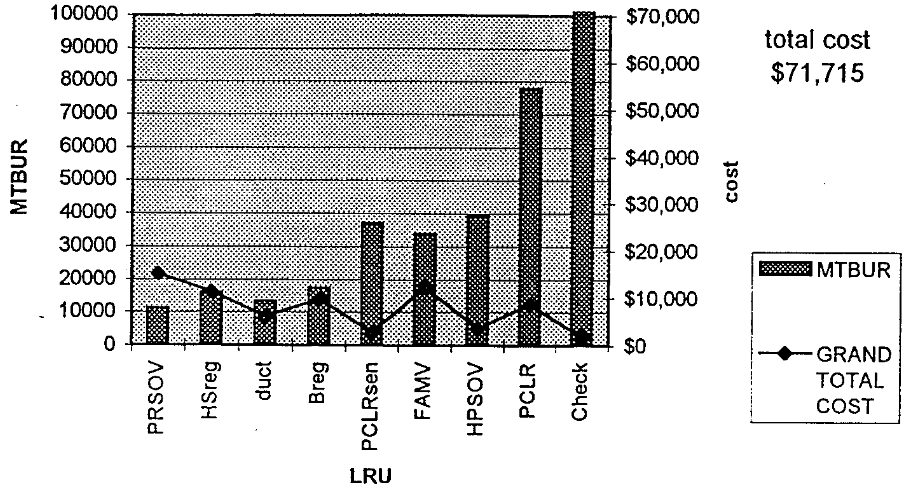
LRU	indication	% of FR	failrateperind
famv	28	25	7.3945
	2368	5	1.4789
	57	70	20.7046
check	2	100	1.34
HSreg	1	45	16.9515
	136	10	3.767
	2	35	13.1845
PCLRsen	2	25	4.20125
	236	5	0.84025
	5	70	11.7635
Breg	1	55	23.69235
	2	35	15.07695
Thermo	2	10	0.9058
	36	90	8.1522

Totals

sum FRn-i column Tot Failrate n-i	1/Tot FRn-i *1e6 Tot MTBF n-i	sum FRu column failratei-un	1/FRiu *1e6 MTBUR i-un	MTBFi MTBUR i-j
44.11435	22668.360748827	20.74234	48210.564	11218.94

	1/(1/MTBURun+1/MTBURj) Predicted MTBUR i	Historical MTBUR i
	9101.0574	5394

Figure C7. Spreadsheet calculation and DEPCOST illustration for change 6



LRU	fail rate	MTBF	PC	LLHPR	SLHPR		
hpsov	13.882	72035.73	0.0013882	4.5	4.64		737-300,400,500
prsov	89.135	11218.94	0.0089135	3.05	4.64		
pclr	8.804	113584.7	0.0008804	4	10		prsov
duct	45.455	21999.78	0.0045455	4	2	i=	89.135
famv	29.578	33808.91	0.0029578	7.66	8.92		
check	1.34	746268.7	0.000134	4	1.8		
HSreg	37.67	26546.32	0.003767	3.13	5.38		ch 7
PCLRsensor	16.805	59506.1	0.0016805	2.24	1.53		
Breg	43.077	23214.24	0.0043077	9.94	5.38		
Thermo	9.058	110399.6	0.0009058	4.15	1.39		

		sum FRs per ind	# of candidates	PCi/HPRi normalz	1/failrateind*1e6	sum FRn-FRsind	1/FRn-i	MTBFn-i/PDi	1/MTBURiun*1e6
Indication	candidates	failrateind	Ci	PDi	MTBFind	failraten-i	MTBFn-i	MTBURi-u	failratei-un
1	h,H,B	44.11435	3		22668.4		0	0	0
136	h,H	4.4611	2		224160		0	0	0
2	h,pc,d,c,H,P,B,T	81.967	8		12200		0	0	0
236	d,P	3.113	2		321234		0	0	0
24	pc,d	5.8661	2		170471		0	0	0
245	pc,d	2.24405	2		445623		0	0	0
25	pc,d	1.3493	2		741125		0	0	0
36	d,T	9.0613	2		110359		0	0	0
4	pc,d	2.71295	2		368602		0	0	0
5	d,P	13.12715	2		76178		0	0	0
26	pr	62.3945	1	1	16027.1	0	0	0	0
57	f	20.7046	1		48298.4				

LRU	indication	% of FR	failrateperind
hpsov	1	25	3.4705
	136	5	0.6941
	2	70	9.7174
prsov	16	30	26.7405
	26	70	62.3945
pclr	2	65	5.7226
	24	15	1.3206
	245	10	0.8804
	25	5	0.4402
	4	5	0.4402
duct	2	70	31.8185
	236	5	2.27275
	24	10	4.5455
	245	3	1.36365
	25	2	0.9091
	36	2	0.9091
	4	5	2.27275
	5	3	1.36365

LRU	indication	% of FR	failrateperind	
famv	27	25	7.3945	not listed
	2367	5	1.4789	
	57	70	20.7046	
check	2	100	1.34	
HSreg	1	45	16.9515	
	136	10	3.767	
	2	35	13.1845	
PCLRsen	2	25	4.20125	
	236	5	0.84025	
	5	70	11.7635	
Breg	1	55	23.69235	
	2	35	15.07695	
Thermo	2	10	0.9058	
	36	90	8.1522	

Totals

sum FRn-i column	1/Tot FRn-i*1e6	sum FRiu column	1/FRiu*1e6	MTBFi
Tot Failrate n-i	Tot MTBF n-i	failratei-un	MTBUR i-un	MTBUR i-j
0	N/A	0	N/A	11218.94

	1/(1/MTBURun+1/MTBURj)	
Predicted	MTBUR i	Historical MTBUR i
	11218.938	5394

Figure C8. Spreadsheet calculation and DEPCOST illustration for change 7